Functional analysis of upper-limb movements in the Cartesian domain

Marco Baracca [1,†], Paolo Bonifati[1,†], Ylenia Nisticò[1,†], Vincenzo Catrambone[1], Gaetano Valenza[1], Antonio Bicchi[1,2], Giuseppe Averta[1*], and Matteo Bianchi[1].

Abstract— **The characterization of human upper limb kinematics is fundamental not only in neuroscience and clinical practice, but also for the planning of human-like robot motions in rehabilitation and assistive robotics. One promising approach to endow anthropomorphic robotic manipulators with human motion characteristics is to directly embed human upper limb principal motion modes at joint level, which are computed through functional analysis, in the robot trajectory optimization. This planning method poses some challenges when the kinematics of the manipulator is different from the model used for human data acquisition. In a previous work, we proposed to tackle this issue by mapping human trajectories onto robotic systems relying on Cartesian impedance control. An alternative method could move from the application of the functional analysis to human upper limb kinematics, working directly in the Cartesian domain. In this work, we present the results of this characterization on the data from 33 healthy subjects during the execution of daily-living activities. We found statistical differences between the amount of variability explained by a given number of basis elements in different directions of the Cartesian space. This suggests that some directions of the space are associated with a more complex motion evolution with respect to others, opening interesting perspectives for robot planning, neuroscience and human motion control.**

I. INTRODUCTION

The investigation of human upper limb kinematics is fundamental in different fields, which include neuroscience, clinical practice but also the generation of human like motions with anthropomorphic robots, with important implications also in rehabilitation and assistive robotics [1]. Indeed, human-likeness is an important step to ensure the safety and acceptability of the human-robot interaction. To study the temporal coordinated evolution of human movements, one interesting approach leverages on the application of functional analysis. In a nutshell, the idea is to move from a database of movements collected from humans and to identify a basis of time-series whose combination is able to reconstruct any arbitrary movement. One approach to do this is through functional Principal Component Analysis (fPCA) [2], which can be regarded as a functional extension of standard Principal Component Analysis (PCA). One of the benefits of this approach is that the basis of functions extracted from data is ordered following the amount of variance in the dataset that each function can explain (which is similar to what happens in static conditions with PCA).

More specifically, let us assume a database of movements described in a N-dimensional space: $x(t) : \mathbb{R} \rightarrow \mathbb{R}^N$ where $t \in [0,1]$ is the normalized time. A generic upper limb motion $x(t)$ can then be decomposed in terms of the weighted sum of base elements $S_i(t)$, or functional Principal Components (fPCs): $x(t) \simeq \bar{x} + S_0(t) + \sum_{i=1}^{s_{\max}} \alpha_i \circ S_i(t)$, where $\alpha_i \in \mathbb{R}^{\mathrm{N}}$ is a vector of weights, $S_i(t) \in \mathbb{R}^{\mathrm{N}}$ is the i^{th} basis element or fPC and $s_{\max}$ is the number of basis elements considered. The operator $\circ$ is the Hadamard product, $\bar{x} \in \mathbb{R}^N$ is an average configuration extracted from data while $S_0 : \mathbb{R} \rightarrow \mathbb{R}^N$ is the average trajectory, aka *zero-order* fPC. The output of fPCA, which is calculated independently for each dimension of the space, is a basis of functions $\{S_1, \ldots, S_{s_{\max}}\}$ that maximizes the explained variance of the movements in the collected dataset. Given a dataset with M elements collecting the trajectories recorded in a given dimension j, the first fPC $S_{j,1}(t)$ is the function that solves the following problem

$$\begin{aligned} \max_{S_{j,1}} \quad & \sum_{j=1}^{N} \left(\int S_{j,1}(t) x_j(t) dt \right)^2 \\ \text{subject to} \quad & ||S_{j,1}(t)||_2^2 = \int_0^1 S_{j,1}^2(t) dt = 1 \ . \end{aligned} \tag{1}$$

Subsequent fPCs $S_{j,i}(t)$ are, again, the functions that solve Eq. 1 with an additional orthogonality condition imposed by $\int_0^1 S_{j,i}(t) S_p(t) dt = 0, \ \forall p \in \{1, \ldots, i-1\}$. The core idea is that the output of this process is an ordered list of functions that are organised following the importance that each function has in reconstructing the whole dataset.

Note that this formalization of human trajectories is very compact and full of information, and can enable several practical implementations. For example, one can observe that the higher is the number of functional PCs required to reconstruct one specific movement, the more complex (or jerky) the motion is. This can have a direct impact for the evaluation of motion impairment, for example as a consequence of a stroke event [3], or to design incremental algorithms of human-like motion planning [1]. Indeed, a possible approach to the planning of robotic manipulators is to embed human upper limb principal motion modes at joint level, which are computed through functional analysis, in the robot trajectory optimization. This planning method poses some challenges when the kinematics of the manipulator is different from the model used for human data acquisition. In a previous work, we proposed to tackle this issue by mapping human trajectories onto robotic systems relying on Cartesian impedance control [4]. An alternative method could move from the application of the functional analysis to human upper limb kinematics, working directly in the Cartesian domain. In this work, we present the results of this characterization on the data from 33 healthy subjects during the execution of daily-living activities. We studied the stability of the fPCs in terms of shapes and importance across subjects and across different directions of the movements (intended as translation and orientation of the hand).

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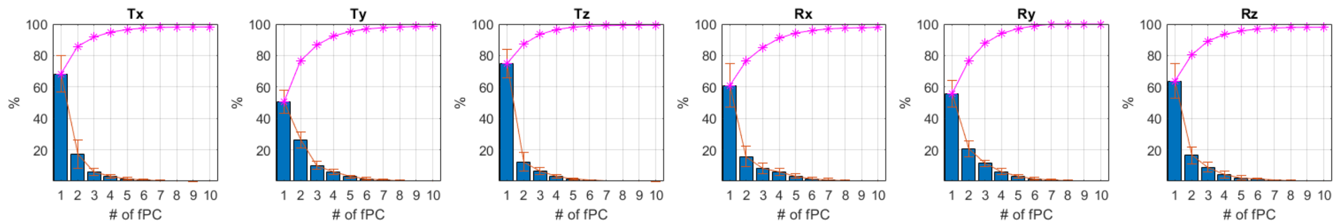

Fig. 1. Variance explained by the first 10 fPCS (blue bars, median and interquartile range) and its cumulative value (magenta line) for each DoF. The label T indicates translations, while label R indicates rotations. The subscript x refers to coronal axis, y to the transversal axis and, finally, z to the sagittal axis.

II. Functional PCs in Cartesian Domain

To study the fPCs in Cartesian domain we leveraged on data (collected in [2]) of 33 healthy participants (17 women, 26.6 y.o. on average, all right-handed) who were asked to perform a set of 30 activities of daily living, each repeated 3 times. Spatial movements of arm, forearm and hand were recorded through optical motion tracking (Phase Space®) using a redundant set of 20 markers fastened to the upper limb. An Extended Kalman Filter was then used to estimate the pose (in term of Cartesian position and orientation with respect to a reference system placed on the torso) of the hand in the 3D space during the whole motion execution. This procedure resulted in six independent DoFs describing the temporal evolution of hand pose during the task execution, three for the position in 3D space (X: upward; Y: rightward; Z: forward), and three for the relative orientation between the hand and the torso reference systems (Euler angles, ZYX parametrization). To enable temporal comparison between different trials, we performed Dynamic Time Warping, i.e. a procedure which maximises the covariation between different trials, ultimately resulting in synchronized signals. More details can be found in [1]. Functional PCA was then used to identify - for each of the six DoFs defining the pose of the hand - the basis of functional components that approximate the variability of the recorded dataset (as in [1], we chose 15 5th order splines). As briefly mentioned in the previous section and extensively discussed in [1], the number of components that are necessary to explain a certain degree of variance in the data is related to the overall complexity of the movement. In other terms, if one DoF requires a higher number of independent components to explain the same amount of variance w.r.t. another, then we can argue that the first DoF is characterized by a more complex behavior. So far, to generate a generic motion using the fPCs, we used the same number of fPCS for all the DoFs of the model. This was justified by the fact that the planning was executed at the joint level. However, knowing in advance whether some DoFs require a lower number of components w.r.t. others may be exploited to simplify the planning problem in terms of number of coefficients to optimize. Furthermore, by working in the Cartesian domain, we could overcome the issue of mapping human functional modes onto robotic systems with dissimilar kinematics.

We observed that there are statistical significant differences between the complexity of the motion for different Cartesian DoFs. Indeed, as depicted in Fig. 1, although a very reduced number of independent fPCs can approximate with high accuracy the human movements in all the DoFs of the hand, which is in line with previous observations [2], there is a not-negligible difference in complexity across DoFs. Indeed, while for T_y the first fPC reaches the 50% of the total variance (50.33 ± 7.387), if we consider T_z, the variance explained by the first fPC is typically higher than 70% (74.85 ± 9.025). Because our data does not satisfy a condition of normality, to prove that differences across DoFs are statistically relevant we performed Wilcoxon rank sum test, which is a statistical non parametric test that can be applied on non-normal data. The comparison was performed for each DoF and for all the subjects, and the p value was then corrected with Bonferroni to compensate for multiple tests. Considering the translation DoFs, our analysis resulted in statistical difference between the variance explained by the first fPC ($p < 0.05$) in all the DoFs except between T_x and T_z. Regarding the rotational DoFs, instead, we observed statistical difference ($p < 0.05$) only between R_y and R_z, while no statistical difference is detectable between R_x and R_y and R_x and R_z. Statistical difference was observed between the variance explained by the second fPC ($p < 0.05$) for all the DoFs of the hand rotation/translation except for differences between R_x and R_z, which are not statistically relevant. Regarding the third fPC, statistical difference between the variance explained was observed between all the DoFs, unless T_x and T_z and R_x and R_z, while essentially no differences can be reported for higher order functional Principal Components (which account for a very limited amount of variability). To verify whether differences are detectable only in terms of ”importance” of fPCs, or also the shape of the components is changed considering different directions (intended here in a general meaning of translations and rotations), we also verified the similarities between fPCs associated to different DoFs, calculated as dot product between vectors. We obtained very high similarities for fPC1, with a mean and std value equal to 0.91 ± 0.15, while the higher order components show an increased variability, i.e. 0.58 ± 0.28 for fPC2 and 0.48 ± 0.27 for fPC3.

These results suggests that a different level of complexity characterizes the movement of the hand in the Cartesian domain. This open interesting questions for future research in neuroscience but also for the planning of human-like movements of companion robots or exoskeletons [1].

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