Human-inspired motion primitives for a safe and effective HRI and autonomous manipulation*

1st Giuseppe Averta
Research Center E. Piaggio
University of Pisa
Pisa, Italy
g.averta3@gmail.com

2rd Matteo Bianchi
Research Center E. Piaggio and DII
University of Pisa
Pisa, Italy
matteo.bianchi@centropiaggio.unipi.it

***Abstract*—Recent advancements in robotics are pushing toward a more strict interaction between machines and their surrounding environment, including humans, in the general framework of *co-botics*, in both industrial and assistive applications. This comes with the need of guaranteeing i) the acceptability of the technology and ii) the users' safety. One of the key characteristics that a co-bot should have to satisfy these requirements is to *behave* as a human would, especially for what concerns the predictability of the robot movements. The intent of our work is to develop a framework for the generation of human-inspired movements for a generic redundant manipulator that works in an unstructured environment. This manuscript reports on recent advancements of our contribution to this line of research, with a special focus on the identification of a basis of motion primitives, which can be used as key ingredients for the planning of human-like motions. Then, we discuss how the feed-forward implementation of these human-like motions can be integrated with a tactile-based feedback policy, when a purposeful interaction with an object happens. These results could open also interesting perspectives for autonomous robotic manipulation.**

I. Human-inspired motion planning

Recent findings in social robotics have highlighted how the human-likeliness (HL) of the interaction between humans and robots is one of the key factors for a safe and effective Human-Robot Interaction (HRI) [1]. One interesting sub-problem is related to the generation of robot movements that can be perceived as HL by the human. This could likely increase the acceptance and the predictability of robotic systems and their behavior. Unfortunately, the generation of HL movements is not straightforward, because humans are characterized by an extremely complex bio-mechanics, especially at the upper limb level, which is made of 206 bones, moved by over 650 muscles. How the brain can cope with this complexity has led to a flourishing literature in motor control (see e.g. [2]) with a strong impact in robotics [3]. Indeed, understanding the basis components of motion coordination has provided significant results in the design [4], the control [5] and the planning [6] of redundant robotic devices, with particular focus on hands.

All these advancements relied on the observation that the neural organization of movements results in task specific co-variation patterns between elemental variables [2]. Interestingly, leveraging on these functional couplings between units it is possible to identify a reduced number of motor schemes, whose combination can approximate the variability of HL behavior, not only in terms of static postures [3], but also for whole motion generation [7], [8].

In our work we have pushed further this approach, by proposing the usage of functional analysis as a tool to identify a small number of motion primitives that represent basis elements, whose combination can reconstruct human movements, with special focus on the upper limb kinematic.

In a nutshell, the idea is to use functional Principal Component Analysis (fPCA) to identify functional primitives from time-varying data [9]. Let us assume to have a dataset of human movements mapped on an arbitrary l-DoFs kinematic model. For each joint, we have N independent observations of joints' temporal evolution $q_1(t),\dots,q_N(t)$ where $q(t):\mathbb{R}\rightarrow\mathbb{R}^l$ and $t\in[0,1]$ is the time (normalized over T evenly spaced time frames). A generic entry of the dataset $q_i(t)$ can be approximated by a weighted combination of functional Principal Components (fPCs) $\xi_j^s(t)$ as in the following: $q(t)\simeq\bar{q}(t)+\sum_{i=1}^{s_{\max}}\alpha^i\circ\xi^i(t)$, where $\alpha^i\in\mathbb{R}^1$ is a vector of weights, $\xi^i(t)\in\mathbb{R}^1$ is the i$^{\text{th}}$ basis element or fPC and $s_{\max}$ is the number of basis elements. The operator $\circ$ is the element-wise product (Hadamard product), $\bar{q}\in\mathbb{R}^l$ is the average of $q(t)$. The principal output of functional analysis is an ordered basis of functions $\{\xi_j^1,\dots,\xi_j^{s_{\max}}\}$ that maximizes the explained variance of the movements included in the dataset.

In particular, the first fPC $\xi_j^1(t)$ can be intended as the vector that solves the following optimization problem:

$$\begin{aligned}\max_{\xi_j^1}\quad & \sum_{i=1}^{N}\left(\int\xi_j^1(t)q_j^i(t)dt\right)^2\\ \text{s. t.}\quad & ||\xi_j^1(t)||_2^2=\int_0^1[\xi_j^1(t)]^2dt=1\ ,\end{aligned}\tag{1}$$

while the other fPCs $\xi_j^s(t)$ are the vectors that solve the same problem of Eq. 1, with an additional constraint of orthogonality, i.e.: $\int_0^1\xi_j^s(t)\xi_j^i(t)dt=0\,,\ \forall i\in\{1,\dots,k-1\}$.

It is interesting to note that - given a desired level of reconstruction accuracy - using the first k functional Principal Components $\xi_j^s(t)$ as motion primitives comes with two major benefits: i) they embed in their shape the key characteristics of human-like motions (bell-shape profile of velocity, low jerk

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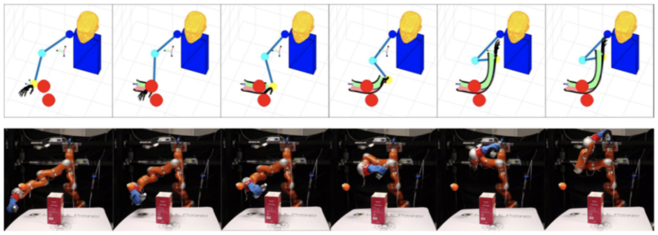

Fig. 1. A Kuka LWR pretending to drink from a bottle. Top: planned motion; Bottom: real motion. Image adapted from [10].

values); ii) these represent the minimum number of independent vectors that can approximate the whole dataset.

Therefore, this definition of motion primitives is particularly suitable for the implementation of a planning problem. Indeed, given a desired initial and final configuration of the kinematic chain, the problem becomes finding the best set of parameters α^i. Such an optimization can be formulated as the following constrained problem:

$$\min_{\bar{q},\alpha_1,\ldots,\alpha_k} \quad J_{\text{task}}(q) \quad \text{s.t.} \quad q(t) = \bar{q} + \sum_{i=1}^{k} \alpha_i \circ S_i(t) \ , \quad (2)$$

where $J_{\text{task}}(q)$ is a generic task-related cost function and k the number of functional PCs enrolled. With this implementation, the search space is narrowed, with the twofold purpose of ensuring human likeness, and strongly simplifying the control problem (because the search space is now of dimension $k+1$). Note that, according to the observations discussed in [6], [7], it is reasonable to expect that a very low number of functional PCs should be sufficient to implement most of the human-like motions at the joint level.

The simple case of a Point-to-Point free motion can be easily implemented through Eq. 2 with the cost function $J_{\text{task}}(q) = ||q(0) - q_0||_2^2 + ||q(1) - q_{\text{fin}}||_2^2$, whose solution can be found in closed form (see [6]. More general cases, in which the robot is also asked to avoid obstacles along the path, can be solved by choosing: $J_{\text{task}}(q) = \left|\left|\begin{bmatrix} q(0) - q_0 \\ q(1) - q_{\text{fin}} \end{bmatrix}\right|\right|_2^2 + \rho P(q, P_O)$, where the first term is responsible to generate a trajectory between the desired initial and final configurations, while the second contribution is a potential-based cost function which maximizes the distance between the robot and the obstacles. Noteworthy, the cost function $J_{\text{task}}(q)$ can even be more general and include other terms to account for other desired motion characteristics (such as energy efficiency).

The trajectories generated through the solution of Eq. 2 are defined on the 7 DoFs kinematic model used to describe the human kinematics. Therefore, to generalize the HL trajectories generated with our approach a mapping problem needs to be solved. Our implementation, presented in [10], proposed to leverage on a Cartesian Impedance controller which minimizes the distance between the planned and the robot end effector. Furthermore, to handle the redundancy, we also included a secondary Cartesian Impedance controller, in the nullspace of the first one to avoid conflicts, which is asked to minimize the distance between planned and real elbow position.

II. Closing the Loop via Tactile Sensing

The HL movements generated through the approach presented in the previous section can be implemented following a feed-forward approach. However, when it comes to interact with the environment or an object, the strategy presented so far needs to be integrated with a feedback policy to partially compensate for errors caused by uncertainties in the estimation of the object properties, such as its position and dimensions. To face this problem, we proposed to include an IMU-based tactile sensing over the back of the fingertips of the robotic hand mounted on the manipulator. The idea, extensively discussed and validated in [11], leverages on the observation that, for each relative direction of contact between the hand and the object, the accelerations exerted on the fingers show different patterns. Therefore, these characteristic signals can be associated with a consequent adaptation of the hand w.r.t. the object in terms of relative re-positioning and re-orientation. Taking inspiration from the observation of human behavior, we extracted a set of 13 reactive primitives which, for each direction of contact, associate a consequent re-arrangement of the hand. Because these primitives are defined at the end effector level, these can be straightforwardly implemented on the robot that, when reaches and contact with an object, will re-orientate the hand to improve the probability to perform a successful grasp (see https://youtu.be/S_771wvvOdY for examples).

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