# Whole-body Motion in Humans and Humanoids

Francesco Nori
Robotics, Brain and Cognitive Science Department
Istituto Italiano di Tecnologia
Email: francesco.nori@iit.it

Jan Peters
Max Planck Institute for Intelligent Systems
& TU Darmstadt, Germany
Email: mail@jan-peters.net

Vincent Padois
Sorbonne Universités, UPMC Univ. Paris 06 and CNRS
Institut des Systèmes Intelligents et de Robotique
F-75005, Paris, France
Email: vincent.padois@upmc.fr

Jan Babic
Faculty of Electrical Engineering
Josef Stefan Institute, Slovenia
Email: jan.babic@ijs.si

Michael Mistry
University of Birmingham, UK
Email: m.n.mistry@bham.ac.uk

Serena Ivaldi
TU Darmstadt, Germany
Email: ivaldi@ias.tu-darmstadt.de

***Abstract.*** Traditional industrial applications involve robots with limited mobility. Consequently, interaction (e.g. manipulation) was treated separately from whole-body posture (e.g. balancing), assuming the robot firmly connected to the ground. Foreseen applications involve robots with augmented autonomy and physical mobility. Within this novel context, physical interaction influences stability and balance. To allow robots to surpass barriers between interaction and posture control, forthcoming robotic research needs to investigate the principles governing whole-body motion and coordination with contact dynamics. There is a need to investigate the principles of motion and coordination of physical interaction, including the aspects related to unpredictability. Recent developments in compliant actuation and touch sensing allow safe and robust physical interaction from unexpected contact including humans. The next advance-

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ment for cognitive robots, however, is the ability not only to cope with unpredictable contact, but also to exploit predictable contact in ways that will assist in goal achievement. Last but not least, theoretical results needs to be validated in real-world scenarios with humanoid robots engaged in whole-body goal-directed tasks. Robots should be capable of exploiting rigid supportive contacts, learning to compensate for compliant contacts, and utilizing assistive physical interaction from humans.

***Keywords—whole-body, control, free floating, interaction, contacts, compliance.***

## 1 Introduction

For cognitive agents, such as humanoid robots, to persist and act in natural human environments, contact and physical interaction become necessary and unavoidable. Everyday tasks involve making and breaking contact, among all areas of the body, whether the contacts are accidental disturbances or intentional support for dynamic movement. Critically, robots should be robust enough to cope with unpredictable contact, via safe control mechanisms and compliance. Moreover, cognitive goal directed robots need the ability to exploit predictable contact, to aid in goal achievement, as well as learn dynamics of contact in order to generalize to novel tasks and domains.

Physical interaction has been studied in robotics, extensively under the umbrella of manipulation. For historical reasons, these studies have assumed a fixed-base as current industrial applications do not necessitate extended mobility. Foreseen robotic applications will demand an increasing level of autonomy, including physical mobility. These applications call for extending studies on interaction to cases where the robot has a mobile-base. Remarkably and differently from the fixed-base case, interaction in these situations may compromise system balance, and goal directed actions require proper whole-body coordination and use of contact. However, the principles governing whole-body coordination in humans are far from being understood and implementations on complex systems, such as humanoids, are missing, especially besides walking.

Within this context one of the major challenges of robotic research is to advance the current control and cognitive understanding about robust, goal-directed whole-body motion execution with multiple contacts. Remarkably, focus should be posed on complex systems, such as humans and humanoids. In a crescendo of complexity, as illustrated in the following figure, current state of the art (state-of-art 1 and 2) should be advanced to address more complex scenarios (challenges 1 and 2).

**State-of-art 1: balancing with multiple rigid contacts.** The robot is standing and balancing with its hands supported by a rigid table in front of its body. However, the table is too fragile, and unexpectedly breaks. A contact state change is sensed, and the robot's control architecture automatically adjusts posture control parameters to main-

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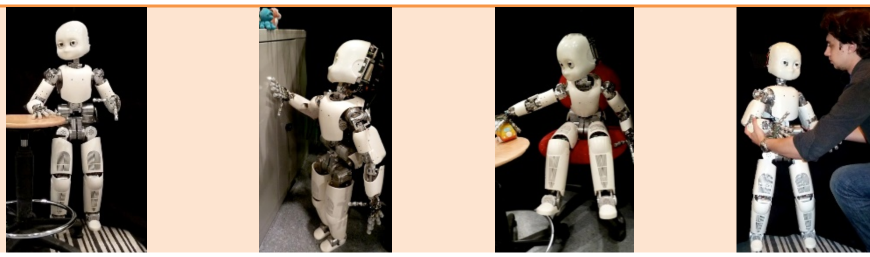
tain balance in light of the reduced support. The unexpected breaking of contact makes it more challenging.

**State-of-art 2: goal directed actions involving contacts.** The robot is standing with its hands at its side, and intends to reach for an object on a table in front. The robot recognizes that the distance is sufficiently far away, and the task cannot be achieved without compromising balance. The robot decides to initiate a new contact with its left hand on the table, providing sufficient support for reaching the object with its right hand.

**Challenge 1: learning non-rigid contacts.** The robot sits down on a chair with a soft cushion, however the cushion has a particular stiffness quality not experienced before. The robot tries to reach for an object on a table, but it fails as it did not adequately compensate for the unexpected dynamics of the soft cushion. After a few attempts, the robot adapts its model of the contact interaction, and is able to infer new control action to successfully reach the goal.

**Challenge 2: human assistive contacts.** The robot is seated in a chair, and a person comes to assist the robot to stand. He/she grabs both hands of the robot and starts pulling upwards. The robot senses the new contact, and recognizing from the interaction force that it is an external agent, allows its arms to be compliant. When the force becomes sufficient to enable standing, the robot recognizes the intended action and stiffens its arms while pushing its legs to rise from the chair. Finally once standing, but still in contact with the human, the robot returns compliance to its arms to allow for safe interaction while retaining overall control of its posture.



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|---|---|---|---|
| **State-of-art 1**. Balancing with multiple rigid contacts. | **State-of-art 2**. Contacts for goal directed actions. | **Challenge 1**. Learning nonrigid contacts. | **Challenge 2**. Human assistive contacts. |

Present day robots are still far from the human capabilities in exploiting predictable events and in coping with uncertainty. The gap between humans and robots is particularly apparent when in tasks involving unstructured physical interaction with the environment or other agents. Recent behavioural experiments yielded a new perspective on modelling the way humans deal with both predictable and unpredictable motor control tasks. In early experiments, it has been shown [55] that humans learn and adapt internal dynamical models of their own arm in interaction with the environment. Such internal models appear to be crucial in predicting how muscle activations produce hand movements and therefore may play an essential predictive role in movement planning. However, Burdet et al. [8] have shown that when prediction is not a viable strategy, humans can rely on arm compliance regulation (by means of muscle

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co-activation) to cope with the unpredictability that naturally arises from feedback delays when performing arm-reaching movements in unstable environments. Basic research and robotics technology are ready to extend such insights from single limb movements to whole-body interaction and the validation of these models appears feasible. In contrast to manipulation scenarios with static base robot systems dynamic whole-body interaction concerns the analysis of phenomena at a higher scale (bigger interaction forces, bigger muscle activations, etc.). whole-body compliance regulation with force/impedance control is not only favoured by current theoretical progress and available technologies, but may actually be ready for wide-spread use instead of being limited to just a few prototypes.

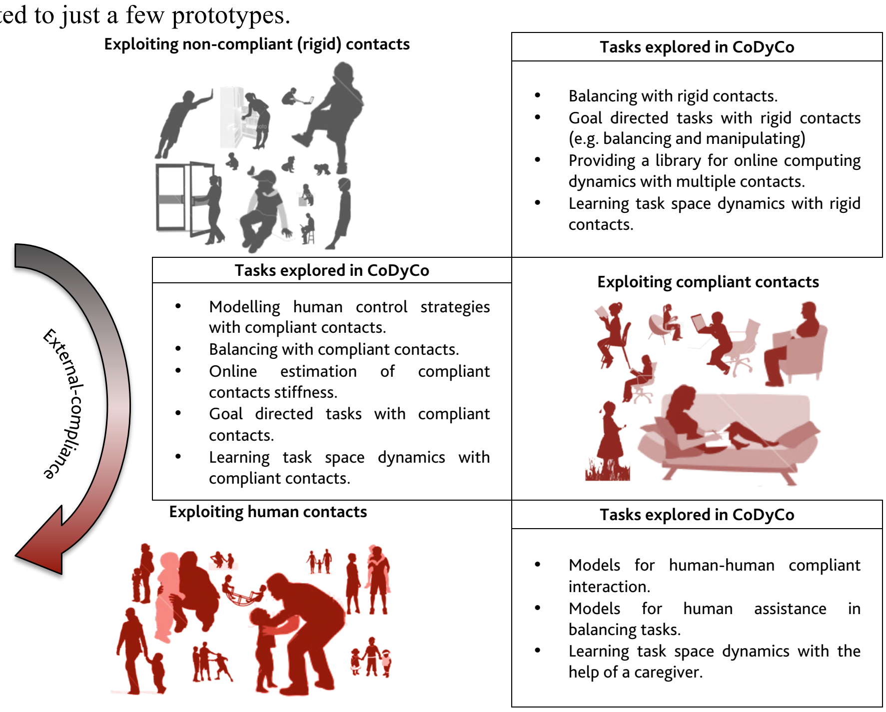


*Figure 1 classification of whole-body tasks based on external-compliance. The complexity increases from top to bottom, i.e., with the need of exploiting the compliance of the contacts.*

*Roadmap beyond state-of-the-art*

With reference to Figure 1 and following, we propose a classification that relies on the well-known concept of *compliance* (or the inverse concept of stiffness), to be understood as the force-displacement characteristic of a contact. Interaction scenarios can be classified by quantitatively measuring two essential components of contacts: *external and internal compliance* (internal here refers to the agent or “the self”). The first scenarios classification (Figure 1) is based on the external-compliance; it includes scenarios that involve non-compliant (rigid) external contacts and scenarios with compliant external contacts. This second category is extremely wide in consideration of the multitude of possible compliant behaviours that can be experienced: from the linear force-displacement characteristic of a linear spring to the complex non-


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linear characteristic of a pillow. Scenarios within this category practically overlap with the first category but rigid contacts are replaced by non-rigid contacts. In these two categories the agent (or "the self", represented with a human silhouette) is always interacting with inanimate objects (the external contacts: a chair, a sofa, the floor, etc.). In the last category, "the self" and "the other" are both humans. In these scenarios the external-compliance is not a well-defined relationship between force and displacement but depends on the active intention of "the other".

External-compliance is only one side of the interaction, and the agent has limited control over it. The other side of the interaction is what we call the "self" (internal) compliance, which is instead fully under control of the cognitive agent. Self-compliance needs to be adapted to the environment compliance and the ability to actively regulate the internal compliance has been only recently implemented on multi-degrees-of-freedom robots. The self-compliance regulation represents the pro-active and cognitive component of the interaction and therefore gives the robot an enhanced degree of autonomy to be exploited in handling situations not anticipated at design time. In this sense, the self-compliance level and actuation range can be used to classify different scenarios as shown by Figure 2. At the very first level of this classification we consider scenarios that do not require significant self-compliance regulation as they typically involve dynamically stable situations. Such situations involve for example dynamically stable tasks, which substantially require direct control of stable postures. The second level of the classification includes tasks that require a certain level of active compliance either to stabilize unstable systems (e.g. balancing) or to compensate for unpredictable interaction characteristics (e.g. standing hand in hand with another agent). Finally at the highest level of this classification we consider highly complex tasks characterized by strong requirements in terms of "self"-compliance planning and regulation.

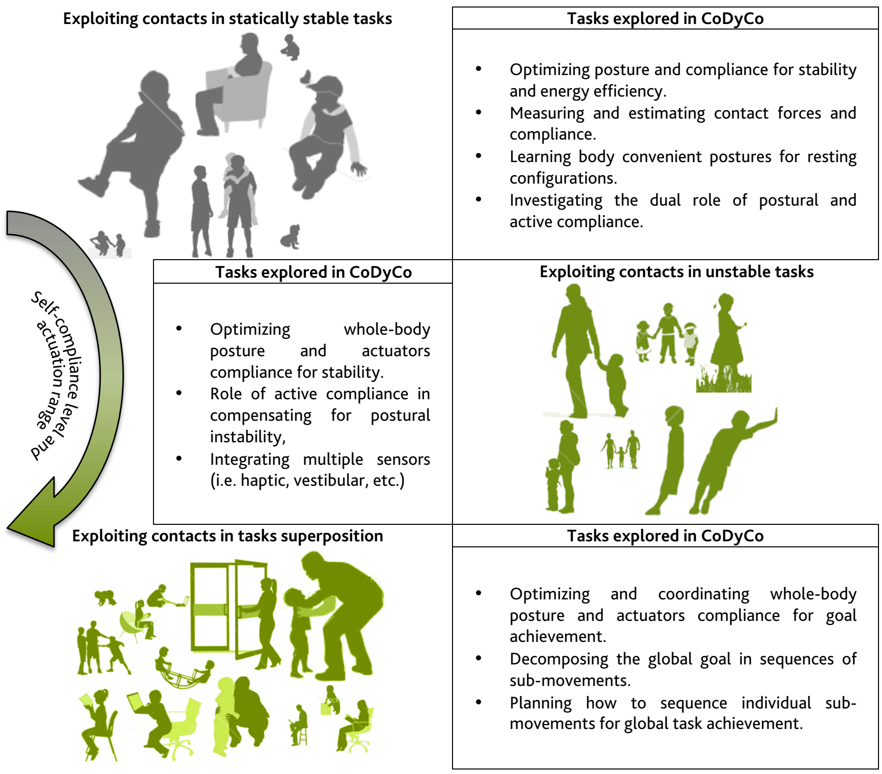


*Figure 2 classification of whole-body tasks according to an increasing self-compliance level and actuation range.*

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External and self-compliance are two fundamental aspects of any interaction. It is therefore crucial to understand how these two concepts become intertwined once contacts are established. We will introduce the concept of **contact-compliance**, which corresponds to the overall compliance obtained once the external and the self-compliance become coupled with the contact establishment. A contact can be seen as the serial connection of two compliances, one representing the external-compliance, the other representing the self-compliance. The compliance of a serial interconnection is simply the linear sum of the individual compliances. Roughly speaking, the contact-compliance does not significantly change when the external and self-compliance are changed simultaneously by an equal and opposite quantity. No advancement can be associated to situations which correspond to augmenting the self-compliance at the cost of diminishing the external-compliance or vice versa, as in these situations the overall contact-compliance does not change. This fundamental procedural principle is well sketched in Figure 3. The horizontal axis sorts possible scenarios according to a progressively increasing external-compliance level. The vertical axis instead orders the same scenarios by means of increasing self-compliance levels and actuation ranges: tasks involving minimal self-compliance regulation or low levels of compliance are shown at the bottom; tasks involving wide self-compliance regulation ranges including high compliance levels are at the top. The grey-colour-valued function shown in the space defined by these two axes is a qualitative evaluation of progress beyond the state of the art: dark grey is the state-of-the-art, increasing levels of blue represent step-by-step progress beyond state of the art. Progress in handling whole body contacts can be achieved only by simultaneously increasing the external and the self-compliance levels. Conversely, little advances are achieved when increasing the environmental compliance but reducing the active compliance component. Vice versa, a dual way to achieve little progress beyond the state of the art corresponds to scenarios that involve a strong self-compliance regulation but reduced external compliance.

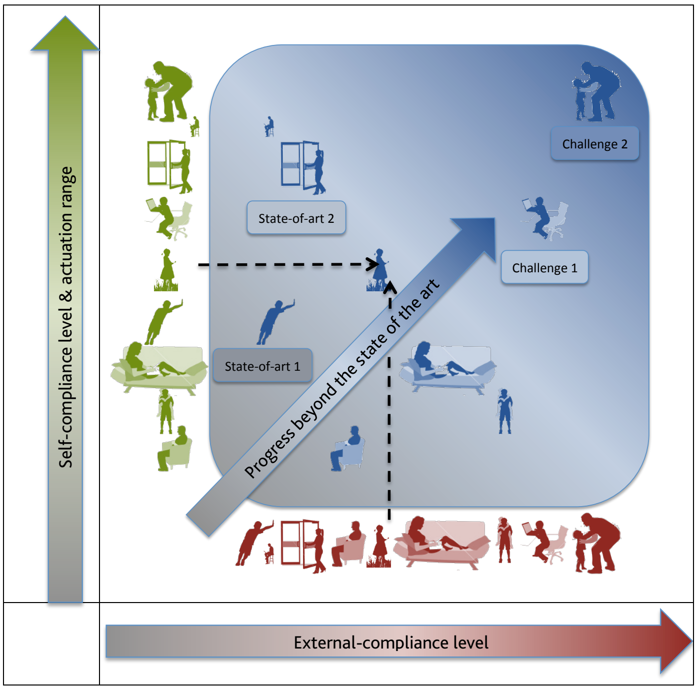


*Figure 3 the metric space to evaluate the progress work beyond the current state-of-the-art. Interaction is the intertwined combination of two components, external and self-compliance, both contributing to the concept of contact-compliance. Whole-body scenarios should be evaluated in a metric space that takes into account how self and external-compliance contribute to contact-compliance. Contact-compliance is the sum of self and external-compliance. Remarkably the major advances can be obtained by simultaneously advancing the external and the self-compliance requirements. The vertical axis represents both self-compliance levels and actuation ranges in consideration of the fact we are mainly interested in self-compliance regulation, actuation and control. The four proposed scenarios have increasing complexity with respect to current state-of-the-art.*

## 2 State-of-the-art

**Technological state of the art.** Among the recent achievements in the field of robotics, there are two major technological prerequisites that will play a fundamental role in enhancing whole-body motion capabilities: distributed force and touch sensing. Both technologies have been only recently integrated and used in (humanoid) robots, including the iCub [35] .

Force control is a fundamental property for any autonomous agent in interaction with the environment. First attempts to regulate interaction forces relied on active force and compliance control schemes, typically coupled with custom mechanical designs such as the ones proposed in [50] and [18] , which were eventually implemented on successful commercial manipulators. Similar solutions have been eventually implemented on some humanoid platforms [9] [14], including the iCub [21] . Recent theoretical and technological advances have revealed the importance of intentionally introducing mechanical compliance in the design [46] and (even more recently) the necessity of actively regulating the actuator passive compliance [28] [58] [36] . It is to be expected that within the next years robots such as iCub will be equipped with variably compliant actuation technologies at some (if not all) of the main joints [59] [60] .

Touch is another fundamental sensing capability for autonomous agents willing to interact with an unstructured environment or humans [5] . Whole-body distributed touch sensing has been only recently embedded on humanoid robots, but there already exist quite a few examples: Robovie-IV [38] , RI-MAN [40] , Macra [18] and Meka [23] , just to cite a few. The iCub already integrates a mature technology [52] covering the upper body, legs and feet soles.

Finally, several open-source software libraries have been developed in the last years to support research in whole-body dynamics and contact simulation. Several dynamics simulators have been developed for robotics (see [22] for a survey). The most interesting physics engines for our purposes are the ones with Featherstone-like forward dynamics calculation [15] [61] , built-in collision detection and stable numerical contact forces computations [42] . Among the kinematic and dynamic libraries it is worth citing HuMAnS[1], a toolbox for analysis and control of both human and humanoid motion, and iDyn, a generic software tool, extensively used in iCub to compute whole-body dynamics and reinforce these computations with measurements coming from sensors embedded in the robot [21] [17] .

**Human motor control state-of-the-art.** Human whole-body motion control has been studied within tasks such as reaching on a supporting surface and sit-to-stand. These movements involve coordination of multiple joints, significant shift of the centre of mass, and control of equilibrium, either in static or dynamic conditions. These are skills learnt early in human childhood but also studied extensively in the context of motor disability, e.g. after neurological insults like stroke, or in the elderly with reduced muscle power, joint flexibility and sensory loss. However, almost nothing is yet known about when healthy subjects choose to make use of contacts with support

[1] http://www.inrialpes.fr/bipop/software/humans/index.html

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surfaces. It has been shown that in standing posture, this contact provides augmented sensory information reducing sway [25] , and how in some circumstances, non-weight bearing but informative “light-touch” between two standing subjects can cause coupling that leads to increased sway, emphasising that knowledge about the stability and compliance of the contact surface is vital.

*Reach using supports.* Human reaching with arm support has not been extensively studied. There is almost no literature on the issue of how humans use one hand to extend their reach space. For example, to lean forwards requires a shift of the trunk and a shift of the centre of mass [20] . At some point it becomes advantageous to use a supporting surface, allowing a reduction in anticipatory postural adjustments and a simplified control strategy [56] . But the decisions about when to implement support using one arm, which will depend on the availability, reliability and compliance of a support surface are almost unstudied [29] .

*Sit-to-stand.* The postural adjustments that contribute to a sit-to-stand action are well documented. The action requires a shift of centre of mass, development of momentum, and precisely timed hip and knee extension, combining with maintaining stability with ankle control. As motor ability lessens, e.g. in the elderly, compensatory foot placement with increased momentum generation using hip flexion and arm movement is often employed [24] . Support from the chair arm or from a cane [33] increases stability in the forward axis. Again, decisions about when the support surface would be used, depending on its stability and compliance, are unstudied. The effects of unstable foot support in the sit-to-stand action are studied in [20] the authors suggests a clear trade-off between support surface stability and manoeuvrability, and argue that adapting to the added uncertainty could help individuals become more manoeuvrable. Finally, there is little work on how the sit-to-stand action changes with elastic support - this has been studied in locomotion and jumping [4] , but not in interactions with support surfaces.

*Dimensionality reduction.* Complex multi-joint movements call for control strategies that simplify and reduce degrees of freedom. There are various competing theories of how this can be achieved [31] . Perhaps most relevant is the uncontrolled manifold hypothesis [53] that demonstrates that it is highly effective to allow some parameters to be uncontrolled, if task irrelevant, and to control only a fewer task relevant parameters. In [53] Scholz & Schoner applied this to the sit-to-stand task, and show that the centre of mass in the forward axis is well controlled, head and hand position are less controlled, and vertical head position appears little controlled. How these behaviours change with support is an open question. Equally important is the issue of how high dimensionality whole body motion of human models can be reduced to extract principles of action applicable to robots with different geometries. These are implemented by muscle and joint synergies that reduce the functional degrees of freedom during a given action. There has been very effective use of principal or independent components analyses to capture such human whole body movement and reduce dimensionality (e.g. as in [16] ). Recent developments include extracting functional components, which treat joint-kinematics data as functions instead of as a series of independent samples, and are comparable across groups of subjects [10] .

**Robot Motor Control state of the art.** In complex scenarios, when the robot and the environment are assumed to be perfectly known, planning approaches explore the possible states of the robot (e.g. configurations of the robot in its environment) in probabilistic graph-like manners [32] to determine the sequence of commands to provide to the robot to perform a certain action in free space [12] [30] or in complex contact situations [6] [7] . Such methods are usually computationally demanding and difficult to apply online. Conversely, when the global goal of the robot is relatively simple, the high-level planner can be almost disregarded because the goal to be achieved can “easily” be described a priori in terms of operational tasks [26] to be activated and combined. This falls into “the simultaneous management of multiple operational objectives”, a well-known problem in model-based reactive control. The most popular method to deal with a set of objectives is a hierarchical framework, where operational tasks are typically prioritized in a “stack” [34] , which found several applications to humanoids [54] [37] . QP solvers have recently gained popularity in humanoid robotic as they do not require the explicit inversion of any model of the system [2] [11] [14] [48] . This corpus of reactive methods mostly succeeds in overcoming the "complexity and uncertainty" factor thanks to the use of feedback. However the proposed solutions are only locally optimal and the overall decision-making process cannot be addressed in the most general cases (i.e. without scripted scenarios). There is obviously a need for approaches where planning and reactive control are combined in a strongly intertwined way. This is not a simple problem: there are very few works where such a combination has actually been tested in a non ad hoc manner. The work of [3] contributed to describe the necessary control architecture but did not propose any general control solution for such a combination to exist in practice. More recently [45] introduced an architecture combining a whole body control level and a reactive symbolic planning, while [62] focused on dedicated mission-level planning methods for humanoids, coupled to task-level controllers. More recently, [48] [49] have proposed an architecture where sequences of operational tasks are generated on the fly based on a fuzzy-logic, rule-based decision engine. This approach, even though efficient in various specific applications, fails to scale-up as the number of required rules explodes with the growing complexity of the considered scenarios.

**Learning state-of-the-art.** Real-world environments are often hard to capture perfectly with physical models. The uncertainty in model predictions is important during controlled physical contacts between a (humanoid) robot system and its environment. Large errors either in the environmental model or in the task will lead to drastic failures and therefore need to be limited as much as possible by model adaptation. Human-inhabited worlds will never allow perfect modelling and instead require that the system generalizes the tasks in such a manner that they work in a wide variety of different uncertain scenarios where there is contact between robots and either humans or physical objects. Machine learning approaches are therefore needed. Particularly in whole-body motion they are necessary for the successful implementation of the control architecture, and its implementation and application to the real-worlds scenarios. However, off-the-shelf machine learning methods are concerned with static data sets and require massive amount of computations, often rendering real-time learning infeasible. To date, a variety of robot learning approaches have been suggested. The

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most important being model learning, operational space control learning, learning of elementary tasks and hierarchical combinations of tasks, which are briefly evaluated hereinafter.

*Model learning.* High model accuracy and constant model adaptation may be key for low torque interaction during contact. Models of the robot dynamics have been learned by real-time regression, e.g., locally weighted projection regression [51] and local Gaussian process regression [43] . Nevertheless, if any of these approaches would be given the data from a robot in contact with the environment, it would fit the model to this particular case, as the contact forces would just be treated as an additional nonlinearity. As a result, the model will not generalize to new contact models and instead it would be necessary to learn a new model for each type of contact.

*Operational space control learning.* Control in operational space has been approached both as a direct policy learning problem [44] as well as an indirect learning problem via forward models [47] . Here, the problem may be even more drastic as changing the contact formulation will alter the problem in its essence. As a result, an operational space control law may not transfer at all but rather become highly problematic under new circumstances.

*Learning of elementary tasks and hierarchical combinations of tasks.* While learning of contact-free elementary tasks by the combination of imitation learning and policy search [1] [27] is a well-explored topic, no general approaches to date can tackle the exact same problem and allow for different contact combination. Furthermore, learning of hierarchical elementary task combinations is still in its infancy. Several interesting approaches have been suggested [57] [41] [39] [13] in literature, relying on substantially different insights. Further exploration in this area is clearly needed, especially in unexplored multi-contact scenarios.

While all of these frameworks are well motivated in their domains, they have two major shortcomings from the viewpoint of whole-body motion control: they do not explicitly incorporate contact, and they do not leverage on the analytical robotics and control knowledge surrounding them.

## 3 CONCLUSIONS

In this paper we report on the current state-of-the-art in whole-body dynamics studies concerning human movement analysis and robot control. We outline a roadmap of experiments and research questions that are currently explored by the consortium of the European Project CoDyCo, which will provide significant advances in the understanding of the use of contacts both in human motor control and robot control.

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