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ScienceDirect

Physics of Life Reviews 30 (2019) 89–111

PHYSICS of LIFE reviews

www.elsevier.com/locate/plrev

Review

Muscleless motor synergies and actions *without movements*: From motor neuroscience to cognitive robotics

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Received 31 December 2017; received in revised form 12 April 2018; accepted 16 April 2018
Available online 27 April 2018
Communicated by J. Fontanari

Abstract

Emerging trends in neurosciences are providing converging evidence that cortical networks in predominantly motor areas are activated in several contexts related to 'action' that ***do not cause any overt movement***. Indeed for any complex body, human or embodied robot inhabiting unstructured environments, the dual processes of shaping motor output during action execution and providing the self with information related to *feasibility, consequence and understanding of potential actions* (of oneself/others) must seamlessly alternate during goal-oriented behaviors, social interactions. While prominent approaches like Optimal Control, Active Inference converge on the role of forward models, they diverge on the underlying computational basis. In this context, revisiting older ideas from motor control like the Equilibrium Point Hypothesis and synergy formation, this article offers an alternative perspective emphasizing the functional role of a 'plastic, configurable' internal representation of the body (body-schema) as a critical link enabling the seamless continuum between *motor control* and *imagery*. With the central proposition that both "real and imagined" actions are consequences of an internal simulation process achieved though *passive* goal-oriented animation of the body schema, the computational/neural basis of ***muscleless motor synergies*** (and ***ensuing simulated actions without movements***) is explored. The rationale behind this perspective is articulated in the context of several interdisciplinary studies in motor neurosciences (for example, intracranial depth recordings from the parietal cortex, FMRI studies highlighting a shared cortical basis for action 'execution, imagination and understanding'), animal cognition (in particular, tool-use and neuro-rehabilitation experiments, revealing how coordinated tools are incorporated as an extension to the body schema) and pertinent challenges towards building cognitive robots that can seamlessly "act, interact, anticipate and understand" in unstructured natural living spaces.

Keywords: Synergy formation; Motor imagery; Forward/inverse models; Body schema; Tool use and motor skill learning; Embodied cognition

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https://doi.org/10.1016/j.plrev.2018.04.005

1. Introduction

Even during common daily activities like dining together, playing a game, using a tool, assembling an object from constituent parts etc., we effortlessly generate dexterous actions, predict potential consequences' of possible actions of oneself (and others). Emerging trends in motor neurosciences now provide converging evidence that seemingly disparate functions of action 'generation, simulation, and observation' consistently engage an overlapping network of cortical areas in the predominantly motor region of the brain (see Ptak et al. [86], Pickering and Clark [78], Grafton et al. [42], Pulvenmuller [77], Gallese and Sinigaglia [41], Kranczioch et al. [60] for reviews). The general insight emerging is that the fundamental problems of shaping motor output during action execution and providing the self with critical information related to feasibility, consequence and understanding of potential actions are closely intertwined than previously conceived. From an evolutionary perspective too, in any organism with complex body (human or embodied robot) inhabiting unstructured environments, *actions are 'goal oriented' and not just stimulus oriented*. This fundamentally requires 'covert simulation and overt execution of action' to incessantly alternate during the evolution of purposive behaviors and social interactions. In this sense, real and imagined actions are like Siamese twins, inseparable but to some extent independent. How is this delicate balance realized in the brain? How are cortical substrates basically involved in organization of overt action functionally 'recycled' in other contexts (i.e. actions without movements)? While the prevalent computational modeling approaches generally converge on the role of internal models, they diverge on the perspective of how they might be realized in the brain (Pickering and Clark [78]) or modeled computationally (Friston [29]).

Revisiting older ideas from motor control like the **Equilibrium Point Hypothesis (EPH)** and synergy formation (Bernstein [8], Asatryan and Feldman [2], Bizzi et al. [13], Abend et al. [1]) in the context of emerging trends in motor neuroscience, this article offers an alternative perspective emphasizing the functional role of a 'plastic, expandable' internal representation of the body i.e. the 'body schema', as a fundamental connecting link to facilitate the seamless continuum between motor control and motor imagery. In general, synergies are often associated with muscles and actions with movements. *Instead, we posit that muscleless motor synergies emerging from the goal-oriented animation of the body schema* (*and expandable to coupled tools*) *is the basic mechanism to unify the computational basis of* ***actions with and without movements*** *while we 'act, anticipate and understand'*. The underlying rationale is put in the context of several recent studies in motor cognition in both humans and embodied robots in particular: a) Recording from the parietal cortex in patients undergoing awake brain surgery suggesting the coupling between motor imagery and internal representation of the body; b) Functional imaging studies emphasizing the shared cortical basis for 'execution, imagination and understanding' of action; c) Studies related to tool-use learning, revealing how tools are incorporated as an extension to the body schema during coordination, highlighting the blurred distinction between tool and the body (other bodies); d) The still pertinent problems in making complex redundant robots more dexterous, cognitive and social: opening up practical issues like need for computational simplicity, task specific configurability, effective human robot interaction; e) How all of this influences our understanding of synthesis of overt movements itself, a pertinent topic that has also been in recent debate. The next subsections review the literature and various issues related to coordination of a complex body (human/robot) inhabiting unstructured environments and their link to muscleless motor synergies and simulation of action to support goal directed reasoning and social interaction.

1.1. Coordinating a complex body (human or embodied robot): problems, solutions and synergies

Unlike the range of direct problems in conventional physics (like computing effects of forces on objects), during the production of common day to day movements our brains have to deal exactly with the inverse problems of determining muscle activations, joint rotations, movement trajectories, speed profiles that would allow the desired goal-directed interaction with the environment. Strikingly, many of the inverse problems faced by the brain to control movements are indeed similar to the ones roboticians must solve to make their robots move dexterously. Note that, while coordinating any complex body (human or robot), the underlying control system has to deal with two typically contrasting requirements: the need to choose 'one' from infinite possible solutions (Bernstein's *Degrees of Freedom problem*) and the need to produce 'one solution' in an infinite number of ways (Lashley's *Principle of Motor equivalence*). As a simple example, even the task of aimlessly moving the finger from one point to another can be achieved in an infinite number of ways (motion trajectories, joint rotations, speed profiles, muscle activations). Further in most manipulation tasks, the solution must be compatible with a combination of multiple *bodily* (joint limits, torque limits etc.) and *task specific* (desired end-effector pose, obstacles etc.) *constraints*. How does the brain deal with this 'problem of plenty' and how can embodied robots efficiently coordinate their complex bodies to generate dexterous goal oriented movements? The present understanding of the plausible underlying computational basis is broadly based on three interrelated yet diverging frameworks i.e. Optimal Control (OCT: Diedrichsen et al. [34], Todorov [88]), Active Inference (AI: Friston [29]) and Equilibrium Point hypothesis (EPH: Asatryan and Feldman [2], Bizzi et al. [13]), see Pickering and Clark [78], Mohan and Morasso [66] for reviews on the pros and cons and interrelations between these approaches.

While OCT has emerged as a dominant theory for interpreting a range of motor behaviors (Scott [91], Li [92], Chhabra et al. [93], Shadmehr et al. [34], Harris and Wolpert [49], Kording et al. [59]), online movement corrections (Saunders and Knill [111]; Liu and Todorov [112]), structure of motor variability (Guigon et al. [94]), Fitts' law and control of precision, and coordinating anthropomorphic robots (Nori et al. [95], Kumar et al. [96], Ivaldi et al. [55], Parmiggiani et al. [74], Fumagalli et al. [38]), several open questions like the massive computational cost to perform the necessary complex optimizations especially in highly redundant systems like robots and humans (Doya [98], Friston [29]), hence the neuro-biological plausibility (Todorov [97]), the nature of the cost function itself given that multiple cost functions (minimum jerk, torque change, end point variance, object crackle etc.) make similar predictions on basic qualitative characteristics of movement and the issue of sub-optimality (Kodl et al. [99]) have been in recent debate.

In this context, multiple authors (Friston [29], Mohan and Morasso [66], Herbort and Butz [101], Pickering and Clark [78]) have raised an even deeper pertinent question *i.e. do muscle activations cause joint rotations that cause the end effector motion 'or' is it the other way round?* This perspective sounding like the classical 'chicken vs. egg' problem draws upon ideas from different disciplines like active inference and predictive coding (Friston [45], Kilner [48]), Ideomotor theory (Herbort and Butz [101]), the EPH (Feldman and Levin [37]), and has at least three following ramifications towards shaping our understanding of coordination of action in humans/robots:

(a) ***Computational cost/simplicity*****:** this line of thinking converts an 'ill posed' problem of motor control (one from many) into a 'well posed' problem (one to one) thus circumventing the need for explicit kinematic inversions (Mohan and Morasso [66], Pickering and Clark [78]) and cost function computations that can be prohibitive for example while coordinating a 53-DoF humanoid;

(b) ***Real and imagined actions*****:** the idea of action being understood as consequences of our own predictions concerning the flow of sensation i.e. a version of the Ideomotor theory of James [46] and Lotze [47], resonates with emerging studies form neurosciences suggesting that action 'generation, perception, simulation' share cortical substrates (thus complementing (a));

(c) ***Embodiment*****:** emphasizing that it might be possible to simplify the computational process of coordination of action by actively exploiting properties and constraints of the physical system that is being coordinated (like, stiffness, compliance, reflex, local-to-global distributed processing) drawing upon ideas from EPH and Embodied simulation (hence complementing (a) and (b));

These topics (a)–(c) will be connected gradually with both empirical studies from humans and experiments with robots as we progress.

1.2. Computing with the body: muscle synergies and EPH

A general concept that was in the background of many studies to explain neural control of movement during the mid-60s to mid-80s was the Equilibrium Point Hypothesis (EPH: Asatryan and Feldman [2], Feldman [36], Bizzi et al. [10,13], Feldman and Levin [37]). Innovative aspects of the EPH was its strong grounding in the biomechanics of the body and the apparent computational simplicity in solving the degrees of freedom problem. *The basic Idea was that posture is not directly controlled by the brain in a detailed way but is a 'biomechanical consequence' of equilibrium among a large set of muscular and environmental forces*. In other words, complex actions can indeed be achieved (i.e. choosing of one from many) *without* a complex, high dimensional optimization process by simply allowing the intrinsic dynamics of the neuromuscular system to seek its equilibrium state when trigged by *intended goals*.

The EPH idea exploited two beneficial properties of the neuromuscular apparatus of the body: 1) to induce, locally (in a muscle-wise manner), an instantaneous disturbance compensation action, and 2) to induce, globally (in a total body-wise manner), a multi-dimensional force field with attractor dynamics. Numerous studies carried out with intact and spinalized animals (Bizzi et al. [12], Mussa-Ivaldi and Bizzi [102], d'Avella and Bizzi [6], Bizzi and Cheung [11], Roh et al. [103], Berniker et al. [7]) demonstrated that complex motor behaviors can be constructed by muscle synergies, with the associated force fields organized within the brain stem and spinal cord, and activated by descending commands from supraspinal areas. Muscle synergies were also shown to be correlated to the control of task-related variables (e.g. endpoint kinematics, displacement of the center of pressure; Ivanenko et al. [104], Torres-Oviedo et al. [87]).

On the other hand, it is still an open question whether or not the motor system represents equilibrium trajectories (Karniel [58]). Motor adaptation studies, starting with the seminal paper by Shadmehr and Mussa-Ivaldi [81], demonstrate that equilibrium points or equilibrium trajectories per se are not sufficient to account for adaptive motor behavior, but this is not sufficient to rule out the existence of neural mechanisms or internal models capable of generating equilibrium trajectories. Rather, as suggested by Karniel [58], such findings should induce the research to shift from the lower level analysis of reflex loops and muscle properties to the level of internal representations and the structure of internal models. This viewpoint is also supported by recent electrophysiological experiments in the lower vertebrates, cat, and monkey that provide evidence that the temporal activations of muscle synergies identified by computational algorithms are ultimately expressions of neural activities.

In this context, only recently advanced brain imaging techniques have allowed to gain direct access to cognitive/mental states in absence of movement, thus making clear that actions involve a covert stage. In this renewed context, it is worth pondering how the computational principles captured by the EPH idea proposed for coordination of overt movement could be recycled to explain actions without movements and without muscle contractions. Here, a problem with EPH is that, given neural circuits in motor areas are activated in other contexts related to 'action' that do not cause any overt movement, attributing only the intrinsic properties of the musculoskeletal system to explain movement might be a fallacy. Otherwise, as pointed out by Martin [64], reading words like "lick, pick, and kick" would result in licking, picking and kicking. While motor synergies have traditionally been associated with muscles, a way to resolve this conundrum is to take the EPH idea beyond its manifestation 'in flesh' and look instead at 'muscleless' motor synergies and how they could be realized computationally and in the neocortex, so as to support a diverse set of cognitive functions related to action generation, perception, simulation and understanding. This is indeed the motivation of our proposal connecting emerging results from functional imaging, neuro-rehabilitation, tool-use in animals and cognitive robotics.

1.3. Muscleless motor synergies, actions without movements and the body schema

Presently, there is growing consensus that cortical networks in the predominantly motor areas are activated in other contexts related to 'action' that do not cause any overt movement. Emerging studies (see Ptak et al. [86] for recent review) suggests that the dorsal frontoparietal network forms a core system for action emulation, internal representation/manipulation of movement kinematics to support inference in diverse cognitive/social tasks. Distributed multi-center neural activation in the parietal and premotor areas are consistently detected not only during the production of overt movements but also during disparate cognitive functions like observation and imitation of others actions (Frey and Gerry [39], Grafton et al. [82], Iacoboni [52], Rizzolatti et al. [80]), comprehension of language namely action related verbs and nouns (Pulvermüller [77], Pulvermüller and Fadiga [76], Marino et al. [62], Glenberg and Gallese [43], Andres et al. [5]) and action interpretation/perspective taking during social interactions (Decety and Stevens [21], Decety et al. [33], Gallese and Cuccio [40], Koster-Hale and Saxe [57], [100]). The central insight that emerges out of these results is that action simulation and action execution draw on a shared set of cortical networks in the parietal-premotor areas of the brain. Further when observing others actions, people recruit motor representations as if they were themselves acting (Gallese and Sinigaglia [41]). Simply put, understanding may be conceived as an internal simulation that entails the reuse of our own ability to act with our bodily resources in order to functionally attribute meaning to *others'* actions, *importantly recycling some of the same cortical substrates the enable our own selves to act*.

A provocative proposal to explain a shared/recycled 'cortical and computational basis' for covert simulation and overt generation of action is to posit that ***even real movements are consequences of a 'covert internal simulation'***. This idea, formulated in its basic essence in the Mental Simulation Theory of Marc Jeannerod [56] is relevant presently given the trends in motor neurosciences. Undoubtedly, there must be a continuum with the scope of similar computational principles applied at different levels: physical and mental. Even during the generation of overt actions as posited by EPH, *the 'compositionality' of the muscle synergies is ultimately made possible by the 'compositionality' of the underlying force fields and attractor dynamics*. A plausible extension to EPH while retaining its beneficial properties (computational simplicity, biomechanical grounding) and at the same time connect to emerging trends in motor neuroscience is to consider that what occurs in the brain during both mental simulation and overt execution of action reflects an endogenous cortical dynamics very similar to the physical dynamics implicit in EPH, but realized through 'animation' of a 'flexible, plastic and configurable' internal representation of the body, with the attractor dynamics of force fields *induced by the intended goal*. This line of thought is not new but emerged infact during the 80s formally extending the EPH idea from muscles to an internal representation of the body in the brain: body schema (Mussa-Ivaldi et al. [73], Hogan [50], Mohan and Morasso [66], Mohan et al. [65]).

That humans have an integrated, internal representation of their body is strongly suggested by the variety of pathological conditions which can only be explained by a deficient internal representation (Haggard and Wolpert [44], Ramachandran [79], Caeyenberghs et al. [17]) or by sensory illusions (Botvinick [15], Ehrsson et al. [16,28], Lewis and Lloyd [30], [105]). Modern neuroscience has greatly enriched the concept, with numerous studies identifying cortical areas in parietal cortex (Buccino et al. [14]) with multimodal neurons integrating proprioceptive and exteroceptive sensory information to maintain a coherent/updated internal representation of the spatio-temporal organization of the body, see Berlucchi et al. [3], Chiel and Beer [18], Blanke [4] for recent reviews. However, the functional role of the body schema in synergy formation and coordination/simulation of movements has not been investigated in depth. Intriguing insights are now emerging in this direction, particularly in support of body schema being the connecting link between overt and covert action. As Desmurget et al. [31] and Desmurget and Sirigu [32] demonstrate, stimulating right inferior parietal regions (in patients undergoing awake brain surgery) triggers a strong intention to move the contralateral hand, arm, or foot with participants believing that they performed the movements, although *no movement was performed and even no electromyography activity was detected*. Conversely, stimulating the premotor region triggered overt limb movements, though the patients firmly denied that they moved. Such results from direct intracranial recordings from humans highlight, on one hand, the coupling between motor imagery and the internal representation of the body, and, on the other hand, the link between actions with and without movements. Further, the cortical representation of the body is susceptible to plasticity as has been demonstrated from several experiments related to coordinating tools coupled to the body in primates (Iriki and Sakura [53], Maravita and Iriki [61], Umiltà et al. [89]), virtual reality experiments and neuro-rehabilitation studies (Blanke [4], Shokur et al. [83]) where coordinating common tools, virtual avatars and neuro-prosthetic limbs result in task-specific assimilation of such additional Tool DoF into the body schema. During movement generation, the body and the tool act as one cohesive unit, tool effector assuming the role of end effector (like pliers becoming fingers: Umiltà et al. [89]). This analogy can be extended from coordinated tools to other bodies (conspecifics). Recent studies on infants (Marshall and Meltzoff [63]), are also pointing out that body maps in infants facilitate early registration of the similarity between self and the other, a foundation to developing social cognition.

In sum, numerous studies from different disciplines are pointing towards the central function of the body schema in synergy formation, motor imagery, tool use and social cognition. However, the underlying computational basis is still blurred. This issue is highly relevant also in the context of embodied cognitive robotics given that dexterity in overt movement, purposive behavior with anticipation of the consequences of one's actions, *other's actions* are critical desirable features if robots are to become commonplace assistants in numerous application domains: domestic, industrial, elderly care to mention a few. In the following sections, we review both how emerging results from diverse empirical studies summarized so far can guide development of biomimetic architectures for action generation/simulation in cognitive robots and what the interrelations imply on our understanding of neural control of movement in general.

2. The computational basis for muscleless motor synergies: from humans to embodied robots

Why does an embodied robot need a body schema? For the same reason a human or a chimp needs it: simply put, without one, it would be unable to use its 'complex body', take advantage of it, and ultimately survive. Given that the linkage between perception and action is complex (because the body is complex) and is not unique (because the body is redundant), we believe the internal representation i.e. body schema functionally serves as a central building block to simulate interactions of body with the environment, to anticipate the actions of other animate entities and thus effectively plan goal oriented behaviors. While the concept of embodiment has been popular in cognitive robotics (Vernon et al. [84]), the computational basis and functions of body schema in cognitive robots has not yet been addressed in detail (see Hoffmann et al. [85] for a review of the gap between the concept and computational implementations). Note that embodiment and body schema are not the same things: if you have a body schema you also have embodiment but not the other way around. Especially, in light of the emerging results from neurosciences (summarized in the previous section), we believe the body schema is an internal body model shared by real and imagined actions in a way to unify the computational basis of the different aspects of purposive actions: execution, imagery, observation, imitation, understanding.

Let us revisit older ideas from motor control and synergy formation. In the classical view of EPH, *the attractor dynamics that underlies production of overt movement is based on the elastic properties of the skeletal neuromuscular system of the body and its ability to store/release mechanical energy*. However, this may not be the only possibility. The discovery of motor imagery and the strong similarity of the recorded neural patterns in overt and covert movements, it is plausible that attractor dynamics and the associated force fields may not be uniquely determined by physical properties of the neuromuscular system but might arise as well from similar neural dynamics due to interaction among brain areas that are active in both situations. This line of thought resonates with several prominent ideas like internal simulation theory of Marc Jeannarod [56], emulation theory of functional simulation (Hesslow [106]), Ideomotor theory (Herbort and Butz [101]) and embodied simulation hypothesis (Gallese and Sinigaglia [41]). However, a principled computational framework incorporating such ideas and that can be deployed in any embodiment (robots, animated avatars, industrial manipulators though with lesser DoF) to realize diverse cognitive functions related to action generation/simulation is lacking till date.

A simple way to computationally realize such a mechanism is to posit that both overt and covert actions are the consequences of ‘animation’ of a ‘plastic and configurable’ internal representation of the body (human or robot), with the attractor dynamics of force fields induced by the intended goals (and constraints). This concept took shape as the Passive motion paradigm (Mussa Ivaldi et al. [73]) and extension of the EPH idea from muscles to the body schema (Mohan and Morasso [66]). Such an animation process a) offers a low cost solution to coordinate overt movements’ highly redundant systems (exploiting the computational ideas of EPH); b) offers a means to recycle the same computational building blocks to engage in covert simulation of movement for goal directed reasoning and social inference. While formally extending the EPH idea, the emphasis is on the fact that covert and overt stages must represent a continuum, such that every overtly executed action implies the existence of a covert stage, whereas a covert action needs not necessarily turn out into an overt action. The synergistic interaction between the body schema and the attractor dynamics induced by the intended goal could be a means to computationally realize such continuum.

2.1. A plastic, configurable “internal body model” for embodied robots: synthesis, animation and learning

We posit that the computational formulation of the body schema (for both humans and embodied robots) must facilitate mainly:

a) *Somatotopic organization* with relative correspondence among body parts and model components (Berlucchi et al. [3], Hersh et al. [107], Mohan and Morasso [66], Sturm et al. [108]);
b) *Plasticity and learning* so as to incorporate external objects as tool by learning (Maravita and Iriki [61]) and *task oriented configurability* so as to either prune or incrementally recruit various DoF (of the body and coupled tools as necessary).

Such a representation is naturally composed of multiple interconnected body chains (Fig. 1A), available for connection in the context of a task with possibility of extension to couple tools. Some end effectors are ubiquitously used in most daily activities like hands and feet (but other DoF like elbow, head etc. are also flexibly available based on physical and task constraints). The schema/internal representation can be animated by the attractor dynamics of force fields ‘attached’ to one or more body parts/effectors in a goal-oriented fashion to both generate actions (i.e. compute motor commands) or simulate actions (i.e. predict sensory consequences of the actions of self or other bodies by analogy).

Fig. 1B–C depicts three body schema networks of increasing complexity: a simple serial kinematic chain (like a 6 DoF arm or industrial manipulator), an upper body network (i.e. left arm–torso–right arm chain of a human or robot) and a bimanual tool use network (i.e. upper body + coordinated tool).

While the networks get complex from 1B–D, we will use them together to elucidate connecting principles that in our opinion forms the basis for goal oriented synergy formation, action generation/simulation for any ‘body’ (human, humanoid, industrial robots) with arbitrary redundancy and complexity. In particular, we summarize four pertinent

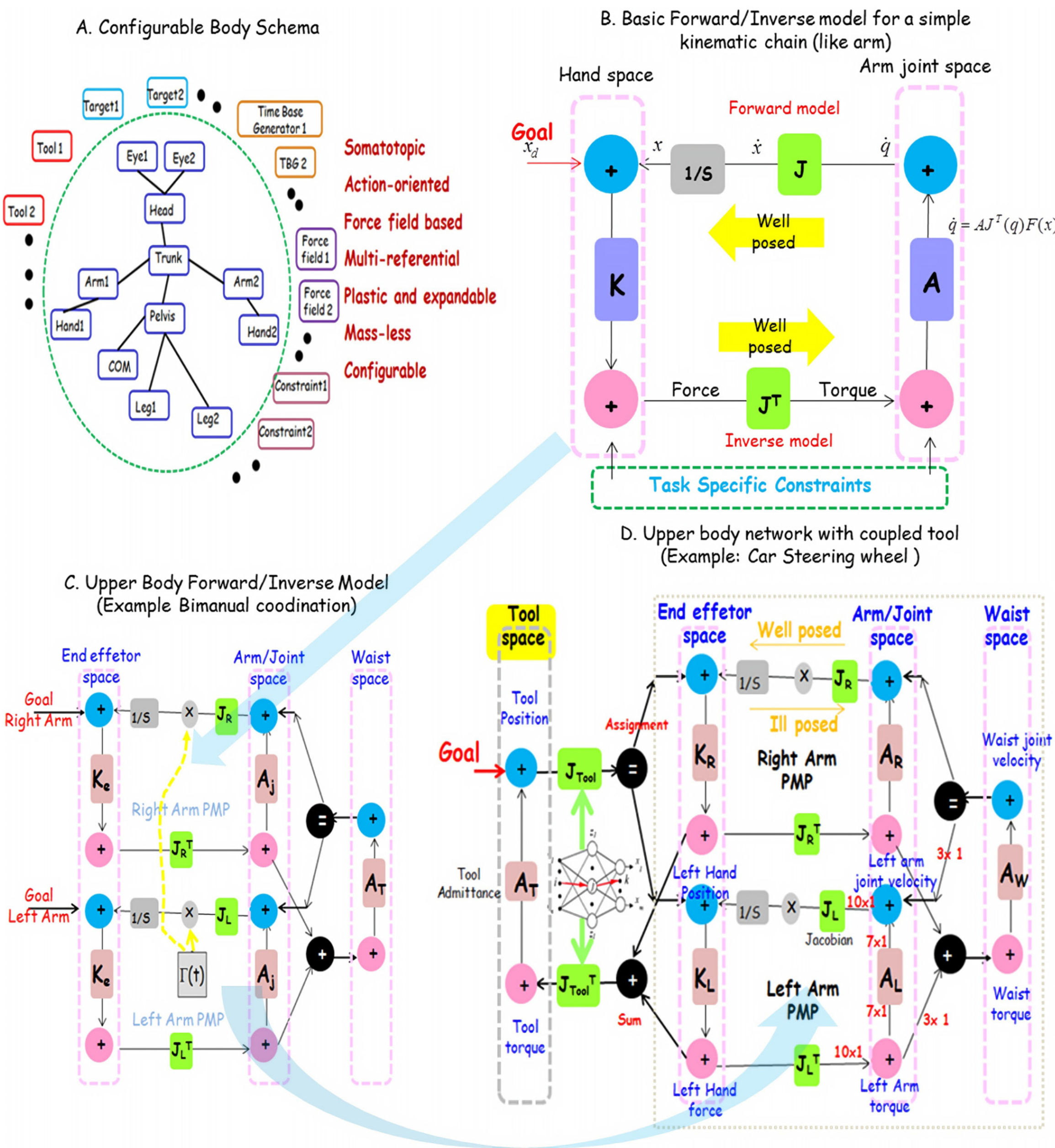

Fig. 1. (A) illustrates the articulated body schema of an embodied robot that is configurable (based on task at hand) and plastic (to incorporate coupled tools) as extension to the body through skill learning. Fig. 1B–D shows three networks of the body schema of increasing complexity for coordinating/simulating a simple kinematic chain (like an arm), whole upper body forward/inverse model (typical in bimanual coordination tasks) and upper body coordination with coupled tool. The three networks are presented together to enable the reader to visualize the underlying modularity (reusing basic building blocks) and common general principles while composing such forward/inverse networks of increasing complexity to be used in diverse motor tasks. Note that the basic sub-network (B) is recycled in (C–D) (upper body coordination, bimanual tool use like steering when control). All networks are grouped into multiple motor spaces involved in the action i.e. tool, hand, arm joint and waist space. Each motor space consists of a displacement (blue) and force node (pink) grouped as a work unit. There are two kinds of connections: Vertical connections (purple) that connect the force and displacement node within a motor space and denote impedances. Horizontal connections (green) connect different motor spaces denote the geometric transformation between them (Jacobian: J). The connecting links can be learnt through a combination of sensorimotor exploration and imitation. Also note that all networks are fully connected, connectivity articulated in a fashion that all transformations are 'well posed': from the joint velocities it is possible to uniquely compute the end effector position (B, C). Similarly, from the force exerted by the two hands (pink nodes in hand space of (D) that are added) it is possible to uniquely compute the tool rotation, but not the other way round. (For interpretation of the colors in the figure(s), the reader is referred to the web version of this article.)

issues: 1) goal oriented synthesis of "body schema networks" at runtime based on the task at hand; 2) the animation of such networks to both generate motor commands to coordinate the body (in case of overt movement) or simulate the consequences (in case of covert movement); 3) how such an internal representation can be learnt so as to seamlessly incorporate other DoF i.e. coupled tools within the same computational framework (and hence reason about them); 4) the possible extension from coupled tools to other bodies during social interactions (to anticipate others actions).

2.1.1. Synthesis of a task specific body schema networks for action generation/simulation

Fig. 1A shows the articulated body schema that in principle encompasses all the DoF's of the body and naturally composed of multiple interconnected body chains. Different parts of the body (i.e. the effectors) are available for connection with various external objects (i.e. tools, other bodies) to perform various tasks. Based on the intended goal, such a representation must be ***configured*** in a task specific fashion (with coupled tools, other task constraints) to realize diverse internal models ***at runtime*** to be used to both compute motor commands (for action execution) or predict the consequences if the action were to be actually performed (hence facilitating goal directed reasoning). Fig. 1B–D shows three such networks of increasing complexity. The three networks are presented together to enable the reader to visualize the underlying ***modularity*** (reusing basic building blocks) and ***common general principles*** while composing such body schema networks of increasing complexity to be used in diverse motor tasks, that we summarize below.

The Basic Ingredients—Nodes, Motor Spaces and Work Units: An interesting aspect of motor control is the multitude of ways in which a single motor coordination task can be described/represented. For example the task of co-ordinating a steering wheel of a car (like Fig. 1D); it can be equally described using mono-dimensional steering wheel pattern or a 6-dimensional hand movement pattern or a 17-dimensional joint rotation pattern or multi-dimensional muscle contraction patterns. Based on the task there are multiple motor spaces involved: for a simple kinematic chain there is a hand space and arm joint space (1A), for upper body coordination the motor spaces include both hands, arm joints and the waist (1B) and a tool space when coordinating coupled tools (1C). In this sense, tools during co-ordination are treated as an extension to the body: tool effector essentially becoming the end effector as substantiated by several studies from tool use in primates (Iriki and Sakura [53], Umiltà et al. [89]), sensory illusions (Ehrrson et al. [28]), coordination of virtual avatars and prosthetic limbs (Shokur et al. [83]), which will be further elaborated in the concluding discussion. All motor spaces consist of two nodes: one representing generalized force (pink nodes) and other representing generalized position (blue nodes). We call the pair of force–displacement nodes as a *work-unit* (*WU*), because the scalar work (force × displacement) is the structural invariant across different motor spaces. In other words, the invariance of energy by coordinate transformations (principle of virtual works) is used to relate different motor spaces. To sum up, in the case of a simple kinematic chain (1B), there are two motor spaces i.e. hand space (with two nodes: representing force and position of the hand) and arm joint space (with two nodes representing torque and rotation of the various joints). The same representational framework is conserved during upper body coordination (1C) and tool use (1D).

Connectivity: One key feature in all the Body Schema networks (1B–D) is their cyclic connectivity that enables every node to reach to every other node in the network. There are only two connecting links i.e. Vertical (connecting the force and position node within a work unit) and Horizontal (connecting one motor space/work unit to another). Take for example a case in Fig. 1C, if we disengage the right arm and the waist space and enter the network at the left arm end effector dx_l and exit at left arm joint space dq_l, we get the following rule for computing incremental joint angles: $dq_l = A_L J^T K_L dx_l$.

Horizontal Links/Geometric Causality: Horizontal links in the network (green blocks) represent the geometric relationship between two motor spaces. This relationship is realized through Jacobian matrices that causally link one motor space to the other. Regardless of connections being serial or parallel, the causal mapping between two motor spaces is generally 'non-linear' and 'irreversible'. However the mapping can be linearized by considering small displacements (or velocities), whose representations in any two motor spaces are related through a Jacobian matrix: for example, $dx_l = J_L(q)dq_l$. Moreover, the irreversibility is dealt with the use of transpose Jacobians rather than computing in the direction inverse to the causal flow. Hence, while the Jacobian maps the small displacements between motor spaces in one direction, the transpose Jacobian determines the dual mapping among forces in the opposite direction (principle of virtual works). For example, in Fig. 1C, the Jacobians J_R and J_L relate the rotations in joints of the two arms and waist into displacements of the two hands, whereas the corresponding transpose Jacobians project the forces F applied on the hands into corresponding joint torques. Similarly in the case of use of tools, a tool Jacobian J_T signifies the geometric relationship between the tool space and the end-effector space to form an interface between the tool and the body for coupled coordination. These tool Jacobians representing the causal relationship between the body and the tool can be learnt by experience with the tool-use via multiple learning streams like imitation, physical interaction and exploration (Mohan and Morasso [68]).

Vertical Links/Elastic Causality: Vertical links in the PMP network signify elastic relationships between forces and displacements and are realized by stiffness and admittance matrices (denoted as K and A respectively). Correspondingly, the links connect generalized force nodes to displacement nodes (or vice versa) in each WU. To account for nonlinearity, Hooke's law of linear elasticity can be used to derive effort from position or vice versa by considering differential variations: $dF = K \cdot dX$ and $dX = A \cdot dF$, where K is the virtual stiffness and A is the virtual admittance. For example, in Fig. 1D, the virtual stiffness K_R and K_L determine the intensity and shape of the force fields applied in the network for right and left hands respectively. For simple cases K is taken as an identity matrix and this denotes an isotropic field, converging to the goal target along straight flow lines. More complex curved trajectories like in case of obstacle avoidance or use of tools, can be obtained by either actively modulating or learning the appropriate values of the virtual stiffness (Mohan et al. [67], Bhat and Mohan [9]). At the same time admittance matrix regulates the contribution of different motor elements to the overall movement in a 'local' way. Every constituent element (for example, a joint in the arm or the waist) responds to the goal-induced 'force-field' based on its own 'local' admittance. But it is finally the overall synergetic balance between the admittances of all joints and not their individual values that direct the net dynamics of the system in achieving the solution. However, the 'local' tunability of the joint admittances allows the overall dynamics to be tweaked in 'task specific' ways. In normal settings, all the joints contributing to the overall relaxation process are considered to be equally complaint. Hence an identity matrix is used to represent the admittance of a motor space, e.g. for a 7 DoF arm, it would be a 7×7 identity matrix. On the other hand, by locally modulating individual joint values, it is possible to alter the degree of contribution of each joint to the overall movement *while not affecting the solution at the end effector space*. The issue of generating different solutions by actively modulating the admittance of different joints has been demonstrated for whole body coordination tasks (Morasso et al. [25,70,72]).

Directionality, Well Posed Computations: A critical issue arises with regards to the *directionality* of the information flow in any cyclic connected network. In Body Schema networks the directionality determines the cost of computation, hence must be considered not only when highly redundant bodies are to be controlled, but also when tools with controllable degrees of freedom are to be coupled to the body. A simple and graceful solution to this issue is that the direction of information flow is constrained by the fact that *such body schema networks* ***always operate through 'well posed' computations/transformations***. Which direction offers 'well posed' transformations is determined by the motor spaces recruited and the type of connectivity between them i.e. Serial or Parallel (this is analogous to electrical circuits).

Serial Connections: Take for example a kinematic chain like an arm that comprises two motor spaces (a low-dimensional end-effector space and a high-dimensional arm-joint space) connected serially. The Jacobian matrix for transformation from joint space to end effector space has more columns than rows (for example, if the end effector state is represented in 3D Cartesian coordinates and the arm has 7 joints, then the Jacobian matrix has 3 rows and 7 columns). In such a case, given the joint angles of the arm, it is possible to compute the position of the end effector uniquely. Hence the transformation from the position node in joint space to the position node in end effector space is well posed. In contrast, the transformation in the opposite direction is ill posed, in the sense that given an end effector position in Cartesian space, it is not possible to compute the value of the joint angles uniquely. This is because the number of available equations is less that the number of unknowns (joint values) leading to infinite solutions. Same is the case with force nodes; the transformation from the end-effector forces to joint torques through the transpose Jacobian is well posed ($T = J^T F$: there are 7 unknowns and 7 equations if the kinematic chain has 7 joints). Conversely, the transformation in the opposite direction is not well posed, i.e. it is not possible to compute the hand forces from a set of given joint torques because there are more constraint equations than unknowns. This sets the direction in the networks of Fig. 1A to flow information from the position node in arm space to the position node in end effector space and the force node in end-effector space to the force node in joint space. In this way, the *cyclic connectivity* in the network is also preserved.

Parallel Connections: Parallel connections are duals of their serial counterparts. A typical biological example of parallel connections is the relationship between the muscles and the skeleton. Given the muscle forces, the problem of finding the joint torque is well posed; however the inverse problem results in infinite solutions. Another example of a parallel connection is that between the two arms and a tool, a steering wheel (Fig. 1D). Generation of a desired steering wheel torque is possible through an infinite combination of forces exerted by the two hands 'in parallel', but the transformation in the opposite direction is unique and hence, well posed. Similarly, it is possible to uniquely compute the position of the two hands for any given steering wheel rotation. Hence in Fig. 1D, there is a force to force transformation from the hand space to steering wheel space, and position to position transformation from the steering wheel space to hand space.

In sum, the directionality of causality in a PMP network is governed by the fact that all computations in the network should be 'well posed'. Operating with well posed computations and circumventing kinematic inversions of a causally noninvertible redundant system significantly simplifies the computational process. Further, since such computations are always well posed and linearized, PMP mechanisms do not struggle with the curse of dimensionality and can be easily up-scaled to any number of degrees of freedom.

Special Nodes for Branching (+/ =): In order to put together multiple kinematic chains through serial and parallel connections to represent complex structures, two additional nodes i.e. Sum (+) node and Assignment (=) node are used to *add* or *assign* displacements and forces from one set of motor spaces/work units to other. For example, in Fig. 1C the assignment node assigns the contribution of the waist in the overall upper body movement towards a goal, to the sub-networks of right and left arms. On the other hand, the net torque experienced at the waist is the 'sum' of torques coming from the right and left arm PMP sub-networks. A sum and an assignment node come as a duo. If an assignment node appears in the displacement transformation between two work units, then a sum node appears in the force transformation between the same work units. This can be understood as a result of conservation of energy between two work units. Similarly, sum and assignment nodes can appear at the interface to couple the body with a tool, as shown in Fig. 1D.

To summarize, with two types of nodes (force and position), two types of connections (geometric and elastic) and some basic rules to direct causality between multiple motor spaces it becomes possible to synthesize incrementally complex networks to represent for diverse motor tasks coordinated by multiple body chains with coupled tools, in a modular, distributed fashion with basic principles recycled. The next two sections summarize how such a body-schema network can be animated to simulate/generate actions and how such an internal representation of the body (and coordinated tools) can be learnt.

2.1.2. Animation of the generated task specific body schema network

The networks of Fig. 1B–D can be animated by attaching force-fields to one or more body parts/effectors in a goal-oriented fashion. The animation process is analogous to the coordination of marionette with attached strings (that represent the attractor dynamics of the force field induced by the intended goal). The computational mechanism involves a process of passive simulation of movement as if it was imposed by an external agent (i.e. the sought goal), in such a way to distribute the desired motion to the global kinematic structure by recruiting joints, actuators, and tools while pulling the dynamical system to the equilibrium state. In the simplest case of reaching, as the end effector reaches the target the rest of the body elastically reconfigures so as to position the end effector at the goal. When motor commands computed by this process of passive simulation are actively fed to the actuators, the robot will perform the motion. Otherwise, the results of such simulation can be used to predict feasibility and consequences of potential actions. While reaching is a simplest case with a fixed point attractor (at the target), the body schema can be animated with moving point attractors to produce diverse spatiotemporal trajectories, as shown in the case of drawing (Mohan et al. [67]), tool use (Mohan and Morasso [68], Bhat and Mohan [9]).

Let q be the set of all the degrees of freedom (DoFs) that characterize the body of a human or robot, possibly extended by including the DoFs of a manipulated object (like a tool). Any given task identifies one or more 'end-effectors' and is defined by the motion $x(t)$ of one end-effector with respect to some reference point. In general, the dimensionality of q is generally much greater than the dimensionality of x. Then the kinematic transformation $x = f(q)$ can be expressed as: $\dot{x} = J(q) \cdot \dot{q}$ where $J(q)$ is the Jacobian matrix of the transformation. Then, the relaxation process in the simplest case for a serial kinematic chain involves the following steps:

(1) *Generate a target-centered, virtual force field in the extrinsic space*:

$$F = K_{ext}(x_T - x) \tag{1}$$

where x_T is the target and K_{ext} the virtual stiffness of the attractive field in the extrinsic space. K_{ext} determines the shape and intensity of the force field. In the simplest case, K is proportional to an identity matrix and this corresponds to an isotropic field, converging to the target along straight flowlines.

(2) *Map the force field from the extrinsic space into virtual torque field in the intrinsic space*:

$$T = J^T F$$

(3) *Relax the arm configuration to the applied field*:

$$\dot{q} = A_{int} \cdot T$$

where A_{int} is the virtual admittance matrix in the intrinsic space: the modulation of this matrix affects the relative contributions of the different joints to the overall reaching movement.

(4) *Map the arm movement into the extrinsic workspace*:

$$\dot{x} = J \cdot \dot{q}$$

(5) *Integrate over time until equilibrium*:

$$x(t) = \int_{t_0}^{t} J\dot{q}\,d\tau$$

The last step integration gives us a trajectory with the equilibrium configuration $x(t)$ defining the final position of the robot in the extrinsic space. ***It should be noted that all the computations in the loop 1–5 are "well posed" and the relaxation mechanism does not require any cost function to be specified in order to solve the indeterminacy related to the excess DoF's (the redundancy problem).*** In the case of a simple reaching task with an arm (using the network of 1B–1C), at the end of the animation process, we get four sets of trajectories (as a function of time): 1) trajectory of joint angles given by the position node in the joint space (arm and waist); 2) the resulting consequence i.e. the trajectory of end effectors given by the position node in end effector space; 3) the trajectory of torques at the different joints (arm and waist), given by the force node in the joint space; 4) the resulting consequence i.e. the trajectory of forces applied by the end effector given by the force node in the end effector space.

At the same time it is possible to integrate a range of internal and external constraints at runtime based on the requirements of the task that needs to be performed, in the form of force fields defined either in the extrinsic space or intrinsic space.

$$\begin{cases} F = F_1(x,\dot{x}) + F_2(x,\dot{x}) + F_3(x,\dot{x}) + \cdots, \\ T = T_1(q,\dot{q}) + T_2(q,\dot{q}) + T_3(q,\dot{q}) + \cdots. \end{cases} \tag{2}$$

A constraint in the extrinsic space could be an obstacle to avoid, an appropriate hand pose with which to reach an object so as to allow further manipulation actions to be performed (like grasp or push). In the intrinsic space a constraint could take into account the range of motion of a joint, the saturation power or torque of an actuator etc.

Time and Timing: There are always temporal deadlines associated with any goal. Control over 'time and timing' is crucial for successful action synthesis, be it simply reaching a target in a finite time or complex scenarios like coordination of multiple kinematic chains (bimanual actions), trajectory formation, multi-tasking etc. A way to explicitly control time, without using a clock, is to insert in the non-linear dynamics of the relaxation process (steps 1–5), a time-varying gain $\Gamma(t)$ according to the technique originally proposed by Zak [90] for speeding up the access to content addressable memories and then applied to a number of problems in neural networks. This mechanism can be applied to any dynamics where a state vector x is attracted to a target x_T by a potential function, such as $V(x) = 1/2(x - x_T)^T K(x - x_T)$, according to a gradient descent behavior: $\dot{x} = -\nabla V(x)$, where $\nabla V(x)$ is the gradient of the potential function, i.e. the attracting force field. Based on the nature of the task, there can either be single or multiple timing signals, hence allowing action sequencing, synchronization, mixing of force fields generated by

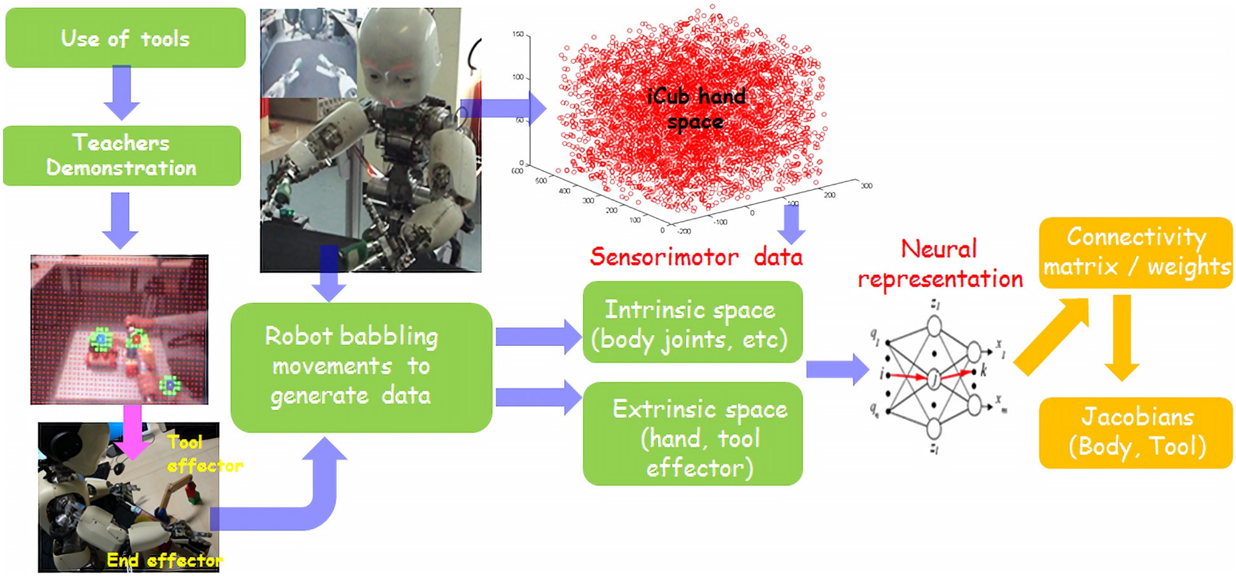

Fig. 2. Shows the block diagram of the information flow to generate data and learn the mapping between different motor spaces (hand space to body joints, hand to tool). The data in the case of the former is acquired by a process of sensorimotor babbling while in the case of latter i.e. tool use can be generated by a combination of imitating the teacher and interacting with the object/tool. A standard backpropagation network is used, and from the learnt connectivity matrix, the corresponding Jacobians are extracted.

multiple spatial goals, generation of a diverse range of spatio-temporal trajectories (Mohan et al. [67]). The timing function can be considered as a kind of "Neural pace-maker" (Zak [90]) and a biologically plausible representation can be identified in the cortico–basalganglia–thalamo–cortical loop and the well-established role of the basal ganglia in the initiation and speed-control of voluntary movements. While in this article, we have restricted to the upper body (as presently deployed in the robot iCub), in a recent article Morasso et al. [70,71] show how the framework can be extended for whole body coordination in humans.

2.1.3. Learning the internal representation of the body (and extending it to coupled tools)

Learning the internal model of the body has been a subject of few interesting studies in cognitive robotics. Hersh and Billard [107] presented an algorithm enabling an embodied robot to visually learn its body schema, knowing only the number of degrees of freedom in each limb. Learning was performed by visually observing its end-effectors when moving them. Sturm et al. [108] developed a model based on Bayesian networks that allows a robot to simultaneously identify its kinematic structure and learn the geometrical relationships between its body parts as a function of the joint angles. The body schema based framework also allows seamless learning of relationship between multiple motor spaces (both the body model) and coupling to coordinated tools, using multiple learning streams (motor babbling, imitation and motor knowledge reuse). Fig. 2 pictorially shows the process to learn both the internal body model and learning to use tools coupled to the body.

In the former case, data is generated by motor babbling while in the latter i.e. extension to tools, the same data (for linking tool to hand space) can be generated by a combination of imitation of the teacher's demonstration, physical interaction with the tool and reuse of past motor experience (see Mohan and Morasso [68,66] for details). For learning the internal body model itself, the robot performs random movements in its workspace always tracking the end effector. This process generates data i.e. the set of arm joint rotation and the corresponding end effector locations (Fig. 2 shows 1.5 K points sampled in the iCub end effector space). Once such data is generated, a standard backpropagation network with two hidden layers learns the mapping $X = f(Q)$. In this case, $Q = \{q_i\}$ is the input vector (of joint angles, in the upper body: in the case of iCub the left arm–torso–right arm chain has 17 DoF), $X = \{x_k\}$ is the output vector (representing 3D position/orientation of the end-effector) and $Z = \{z_j\}$ and $Y = \{y_l\}$ vectors are the output of first and second hidden layer units of the neural network respectively. Equation (3) expresses the mapping, where $\{\omega_{ij}\}$ are connection weights from the input layer to first hidden layer, $\{o_{jl}\}$ are the connection weights between two hidden layers, $W = \{w_{lk}\}$ are the connection weights from the second hidden layer to the output layer, $H = \{h_j\}$ are the net inputs to the neurons of the first hidden layer and $P = \{p_l\}$ are net inputs to the second hidden layer. *Neurons of the two hidden layers fire using the hyperbolic tangent function; the output layer neurons are linear*.

$$X = f(Q) \quad \Rightarrow \quad \begin{cases} h_j = \sum_i \omega_{ij} q_i \\ z_j = g(h_j) \\ p_l = \sum_j o_{jl} z_j \\ y_l = g(p_l) \\ x_k = \sum_l w_{lk} y_l = \sum_l w_{lk} \cdot g\left(\sum_j o_{jl} z_j\right) \\ \quad \Rightarrow x_k = \sum_l w_{lk} \cdot g\left(\sum_j o_{jl} \cdot g\left(\sum_i \omega_{ij} q_i\right)\right) \end{cases} \tag{3}$$

In relation to use of external objects as tools, the same procedure can be applied with the data (end effector motion and the corresponding consequence on the tool effector) acquired also by imitating the teachers demonstration [67,68] thus constraining the domain of random exploration (because a spatiotemporal trajectory comes from the teachers demonstration).

From the Learnt Neural Net to the Jacobians: The critical aspect is that from the learnt weights of the neural network (based on the generated data by different learning streams: babbling, imitation, physical interaction), it is possible to extract the Jacobians encoding the geometric relationship between the respective motor spaces (joint space–end effector space or end effector–coordinated tool effector space) using chain rule (equation (4)).

$$J = \frac{\partial x_k}{\partial q_i} = \sum_l w_{lk} \cdot g^{-1}(p_l) \sum_j o_{jl} \cdot g^{-1}(h_j) \omega_{ij} \tag{4}$$

The internal model of the body itself is constant and is represented by the learnt neural network of the body from which the body Jacobians (that encapsulate the geometric relationship between the end effectors and the internal body joints) can be computed. At the same time, the representation framework is plastic in the sense that while coordinating different tools, the corresponding learnt neural network encapsulating the relation between tool effector and end effector (i.e. the tool Jacobian) has to be loaded from procedural memory to synthesize the task specific 'tool + body network' (like Fig. 1D). In this sense, motor knowledge related to use various tools are learnt and stored in a local fashion, available for connection with the body-schema in a flexible, task-oriented fashion. At the same time, tools during coordination are an extension to the body schema: tool effector essentially becoming the end effector as substantiated by several studies from tool use in primates, coordination of virtual avatars.

To summarize, this section presented the basic computational principles for the synthesis of task specific body schema networks, how such internal models can be animated to both generate motor commands or predict consequences of actions and finally how such an internal model of the body can be learnt and extended to coordinated tools. The next section describes the multifunctional use of the computational framework for action generation and simulation with diverse experiments on 53-DoF robot iCub and two industrial robots.

3. The multifunctional use of the body schema in action generation and simulation

This section illustrates various results related to the use of networks in Fig. 1B–C in diverse tasks ranging from whole body coordination, tool use and simulation of action for goal directed reasoning.

3.1. Body schema networks for action generation

Fig. 3A shows the accuracy of the network in coordinating the 17-DoF robot upper body while reaching–grasping objects in the workspace (using the upper body network of Fig. 1C). The blue cube shows a set of 500 target points in the workspace and the green cube the final hand position obtained when motor commands computed by the animation process (section 2.1.1) is transmitted to the actuators to execute the movement. The Jacobians in the relaxation

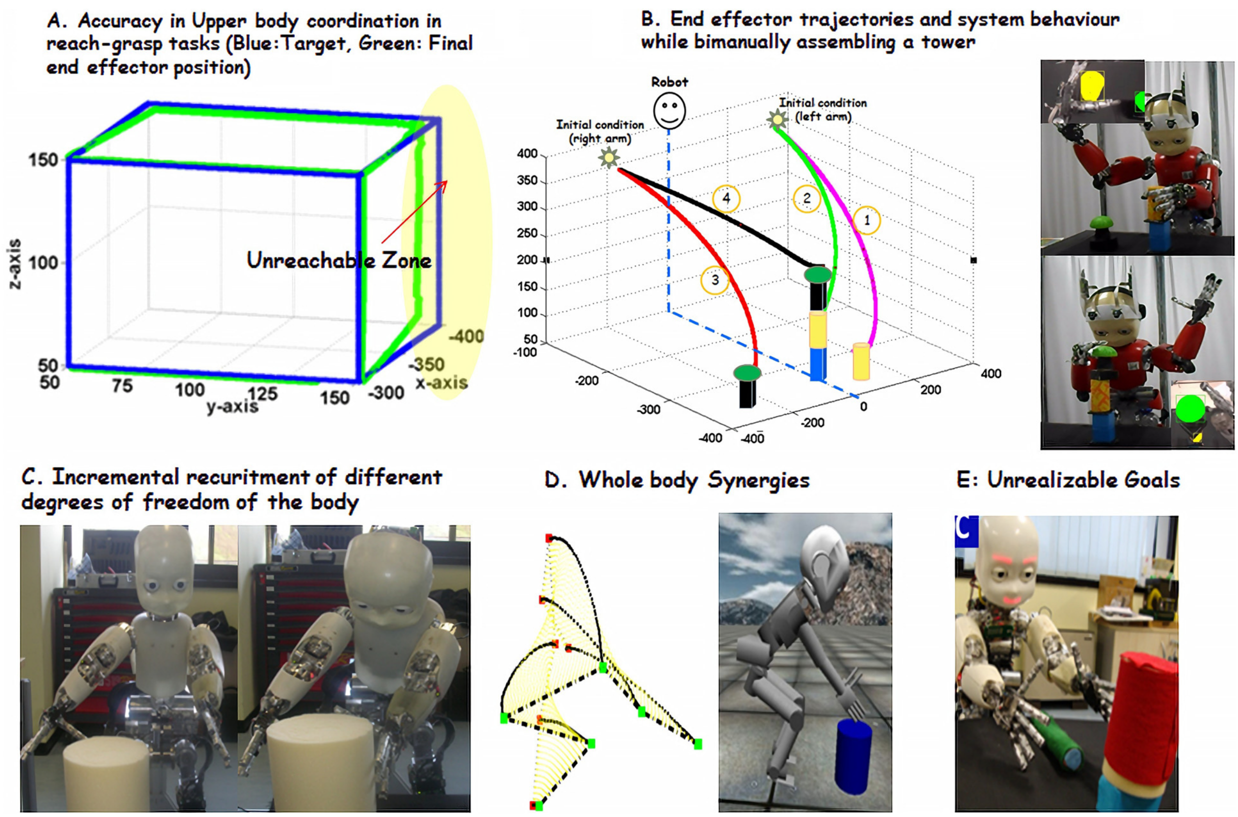

Fig. 3. Illustrates various results related to the use of networks in Fig. 1B–C in unimanual and bimanual coordination tasks with the iCub. (A) shows the accuracy of the network in coordinating the 17-DoF robot upper body while reaching–grasping objects in the workspace. The blue cube shows a set of 500 target points in the workspace and the green cube the final hand position obtained when motor commands computed by the animation process (section 2.1.1) is transmitted to the actuators to execute the movement. Note that even when the targets are unreachable a solution is guaranteed and the robot nevertheless tries to approach the target as much as possible by fully extending the arm to a position that is at a minimum distance from the target. (B) shows the hand trajectories while the robot assembles a tower with three constituent objects. (D) illustrates the concept of grounding with an asymmetric bimanual coordination task. Left panel shows the solution when the network is grounded at the shoulder and right panel when the network is grounded at the waist. In other words, additional DoF freedom can be incrementally recuited during synergy formation. (D) shows the scenario of whole body coordination using both upper and lower limbs. (E) shows the final solution when the goal i.e. to grasp the red cylinder is unrealizable. Such movements need not be executed, instead, the outcome of forward simulation or the residual error can be used to drive further reasoning about other affordances (like the desired length of a tool).

dynamics are computed using the weight matrices emerging from learnt internal neural representation of the body (section 2.1.2). Within the reachable workspace, all the goal targets are reached with a mean variance of 5 mm, thus allowing the robot to inter-act with a range of objects and tools. Importantly, note that even when targets are in the unreachable zone of the body, a solution is guaranteed: the robot nevertheless tries to approach the target as much as possible by fully extending the arm to a position that is at a minimum distance from the target. What we see in such cases is a *gentle degradation* of performance that characterizes humans in the same situations. Although there is no exact solution to the problem, the network "does its best" (see Fig. 3E). In such cases, the non-convergence of the animation provides critical information to reason about affordances of other objects available in the environment (for example, the green stick). Several studies from animal cognition show that a wide range of primates are able to engage in such reasoning about possible tools (sticks, rakes, hooks etc.) to reach unreachable rewards/goals (Visalbergi and Tomasello [109], Weir et al. [110]). Further it is also known that if presented with tools of different lengths during a trial, both corvids and chimps often choose the most appropriate tool directly and do not employ any trial and error based policy. Fig. 1B shows the end effector trajectories of the right and the left arm (position nodes in hand space of 1C) during a bimanual task of assembling a stack (see supplementary information for a video of the assembly). ***Note that all motor commands for action generation are computed without any explicit kinematic inversion or cost function optimization.***

Another interesting observation is the incremental recruitment of additional DoF as necessary (and readily available in a highly redundant body like human or robot). For example, Fig. 3C (left panel) shows the final solution while bimanually reaching the large cylinder (placed far away and asymmetrically with respect to the robot's body) using only both arms with the admittance A_T of the three DoF of the waist (Fig. 1C) is reduced 10 times as compared to the two arms. Simply, without the contributions of the additional DoF of the torso, it impossible to bimanually reach the target. Fig. 3C (left panel) shows the solution when the waist admittance is made equal to the arms. In this case, note the contributions from all three degrees of freedom of the torso, hence enabling iCub to bimanually reach the cylinder successfully in this case. An alternative way to interpret this behavior is that, in the former case the force field induced by the goal did not propagate through the waist network. In other words, the propagation of goal induced force field across different intrinsic elements of the body-schema can be modified by altering their local admittance. This relates to the issue of 'grounding' (similar to electrical networks). Since there are many possible kinematic chains that can be coordinated simultaneously in a complex human/robot body, based on the nature of the motor task it is necessary to identify the start and end points in the body schema between which the force fields generated by the goal will propagate, and beyond which the force fields generated by the goal will not propagate.

3.2. Coordinating coupled tools (as an extension of the body schema)

This subsection depicts the behavior of the 'body + tool' network (Fig. 1D), with an interesting example of bimanually coordinating a toy crane to reach otherwise unreachable goal objects. The fact that the desired goal object cannot be reached/grasp can be inferred from the animation the basic body schema (Fig. 1B–C) at the same time allowing to bimanually grasp the toy crane handle. We now see the behavior of the system when the coordinated tool is coupled to the body in different conditions (normal, pathological) to further understand the internal dynamics and properties of the computational framework. The first aspect to observe is that the representational framework does not make any special distinction between the 'body' and the 'tool'. The tool space is represented exactly in the same manner as any other motor space with a force node and position node (section 2.1), linked vertically by impedance and horizontally by tool Jacobian J_T that is learnt based on the tool and retrieved from memory (section 2.1). During goal directed coordination the body and the tool act as one cohesive unit. The goal now acts on the 'tool effector' which is the most distal part of the extended body schema. The pull of the goal acting on the tool tip is incrementally circulated to the proximal spaces (end effector, arm joints, waist etc.). As the magnetized tip is being pulled towards the goal target, iCub's end effectors are simultaneously being pulled towards the required positions so as to allow the tool tip to reach the goal. These positions are the goals for the end effector space. As a consequence, the joints are concurrently pulled so as to allow the end effectors to reach the position that allows the tool tip to reach the goal. These are the goals for the intrinsic space. If motor commands derived through this incremental internal simulation of action are transmitted to the robot, it will reproduce the motion, hence allowing iCub to perform goal directed movements using the 'body + toy crane' network. This kind of goal-centered functional organization of action is reminiscent of the results of Iriki and colleagues [54], who showed that, with practice, a rake becomes a part of the acting monkey body schema and recent work of Umiltà et al. [89]. Fig. 4 shows results related to goal directed coordination of the toy crane using the extended body schema + tool network. The rows reflect different situations: *normal condition* (*row 1*), *pathological condition* (*row 2*).

In the normal condition (panels 1–4) both the tool is compliant ($A_T = 0.01$) and both arms equally functional to generate force ($K_e = 0.01$ for both arms). The observed behavior is characterized by the following patterns: the green tool angle faithfully tracks the planned red attractor or goal (panel 1); the tool tip is successfully steered to the goal (panel 2); the components of the forces transmitted by the two hands to the tool are approximately bell-shaped and terminate with null values (panel 3); a similar evolution characterizes the torque applied to the tool (panel D) as well as the tool rotation speed. The second row (panels 5–8) illustrates a 'pathological case': the right arm is functionally compromised, in the sense that its force generating capability is reduced. In the reported experiment the elastic coefficient K_e is reduced 10 times (from 0.01 to 0.001 N/m) while retaining the same previous value for the other arm. Panels 5–8 illustrate the resulting behavior: Note that to compensate for the dysfunctional right arm, the left arm generates greater force so as to still realize the goal (i.e. steers the toy crane). Further in spite of the strongly different patterns of force delivered by the two arms (panel 7) the tool tip behaves in a consistent way, although with some error (panels 1, 2) and the tool torque is still approximately bell-shaped (panel 8). Summing up, the synergy formation mechanism has self-adapting properties that allow the robot to exhibit acceptable performance for large

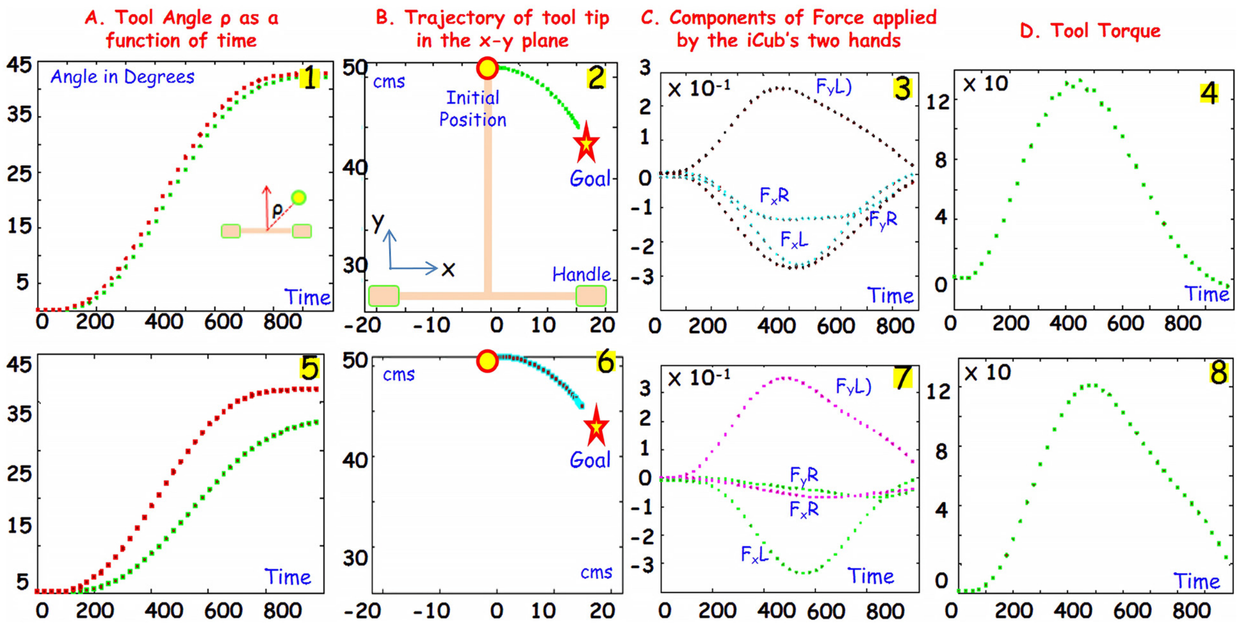

Fig. 4. Row 1: Tool use under Normal Conditions (tool is compliant $A_T = 0.1$, both arms are equally active to generate force $K_e = 0.01$); As seen the tool tip is successfully steered to the goal (panel 2); the components of the forces transmitted by the two hands to the tool are approximately bell-shaped and terminate with null values (panel 3); Row 2: Tool use when right arm functionality is compromised i.e. its force generating capabilities is reduced. (Tool is compliant $A_T = 0.1$, but $K_{e,\text{Right Arm}} = 0.001$, $K_{e,\text{Left Arm}} = 0.01$); Note that to compensate for the dysfunctional right arm, the left arm generates greater force so as to still realize the goal (i.e. steers the toy crane). The synergy formation mechanism has self-adapting properties that allow the robot to exhibit acceptable performance, with a graceful degradation of performance in pathological conditions.

variations of the system's parameters. Remarkably, no learning is needed to accomplish this; it is in fact the property of the attractor dynamics of the 'elastic' body schema system to take into account unaccounted situations and yet do the best in achieving the goal.

3.3. *Actions with and without movements during the evolution of goal directed behaviors*

In this subsection, we present an assembly task to illustrate how covert simulation and overt execution of action alternate, hence facilitating the robot to generate a goal directed behavior to realize an otherwise unrealizable goal. This example also illustrates the joint role of the body schema animation in the prediction of feasibility, consequences of potential actions and generation of overt movements. We believe that such sequences of action simulation and execution are ubiquitous in any goal oriented physical or social interaction. The goal for the robot is to assemble a Fuse Box (Fig. 5A). Note that the task is challenging also in terms of action generation, hence demonstrates the accuracy of the computational model in coordinating the robot.

However, in an unstructured world, the complexity of the environment under which the goal needs to be realized further plays a significant role in the causal sequence of actions an agent must generate to realize its goals. Preprogrammed sequences (like "pick and insert" in this case) very often may not work. In such cases, firstly, there is a need to infer this without blindly executing the standard/default action plan and secondly find alternative plans that transform the environment in a way that makes it feasible to realize the goal. Using the body schema network for the iCub upper body (Fig. 1C) the robot internally simulates the standard sequence of assembly (i.e. picking up the face and inserting it in the body) and its resulting consequence (given by the forward model). These are three simulated actions (Fig. 5B). As seen from the simulated right hand trajectories (1–2), the robot infers that though the 'fuse is directly reachable with the right arm, the 'fuse' is located so far from reach that inserting it will not be successful. This leads to the inference that the goal cannot be directly realized (there is a large error between the attempted goal and predicted forward model consequence). At the same time, the left arm network is not coupled to any goal, so is available as an additional degree of freedom (or tool) that can be used. Coupling part 2 as a goal to the left arm network, the robot

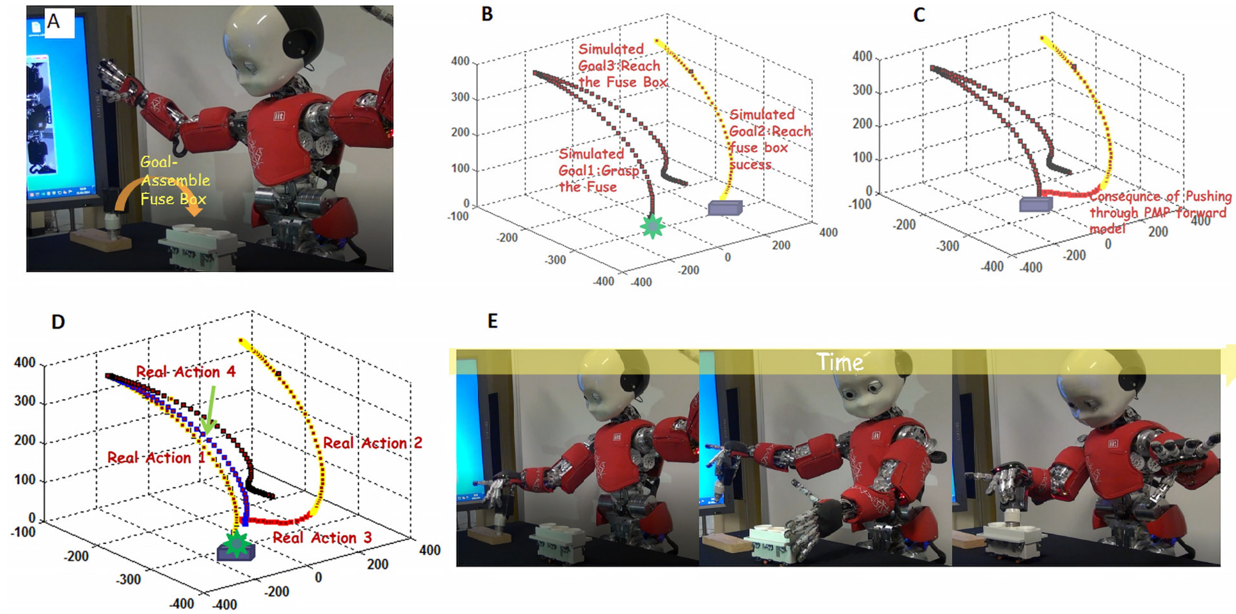

Fig. 5. A–E: The task is to insert "object 1" (fuse) into "object 2" (fuse box), to assemble a fuse box. Panel B shows the first 3 simulated actions using the network of Fig. 1C. In simulation 1 and 3 the robot infers that though the "fuse" is directly reachable with the right arm, the "fuse box" is located so far that inserting it will not be successful. At the same time the left arm network is not coupled to any goal, so is available as a 'tool' that could be exploited. Coupling part 2 as a 'goal' to the available left arm, the robot can infer that the fuse box is indeed reachable by the left arm. Exploiting the knowledge of pushing (learnt in the past and recalled from memory as a feasible action here) the robot infers that if part 2 is slowly displaced close to the "fuse", it then becomes reachable by the right hand. In such an altered environment (Panel C) the assembly goal can be realized. Panel D shows the full combination of real and virtual actions that basically enable the robot to infer how the world can change through ones actions hence make it more conducive towards realization of its internal goals. Panel E shows the sequence of actions initiated by the robot to realize the goal along with perceptual feedback.

can infer that the object 2 is indeed reachable by the left arm (virtual action 3). Information in the working memory indicates that pushing is a feasible action supported by object 2. Interested reader is referred to Mohan et al. [69] for details of how pushing is learnt by the robot. The predicted consequence of pushing is shown in Fig. 5C. The result of simulated actions 1–4 is an 'imagined environment' that allows the goal to be realized. Panel 5D shows the full combination of real and simulated actions. The robot basically uses the left hand to slide the 'fuse box' close to the 'fuse', picks up the face with its right hand and inserts it, hence assembling a composite object and realizing the goal. Fig. 5E shows snapshots of the real actions executed by the robot. In sum, simulated actions allow the robot to infer that while the default plan will not work it is indeed possible to causally transform the world such that it becomes more conducive towards realizing the goal at hand. The simple scenario illustrates the fundamental necessity of action simulation and execution to coevolve during the generation goal oriented behaviors in unstructured setups. At the same time both action simulation and execution emerge from a shared computational substrate i.e. the animation of a configurable body schema.

4. Discussion

The link between the body and its incessant shadow is infact intricately captured in Disney's animated character Peter Pan, with the female protagonist Wendy Darling finally sewing his shadow back to his body. Similarly, connecting the 'metal and wire' body of an embodied robot with its ubiquitous shadow (i.e. an internal representation of its body), this article explored the functional role of the body schema as a connecting link facilitating the seamless continuum between real and imagined action while we 'act, interact, anticipate and understand'. While doing so, older ideas from neural control of movement like the equilibrium point hypothesis were revisited and reformulated in light of diverse emerging results from motor neuroscience. In this concluding section, we briefly discuss the rationale behind the proposed 'animated body schema' formulation in terms of understanding movement in humans and robots: linking evolutionary constraints (complexity of the body and environmental habitats), neurobiological constraints (neuronal reuse in the neocortex, learning), engineering constraints (computational cost, task specific configurability), social constraints (self vs. other) and other prominent approaches in the field.

4.1. Body schema in humans and embodied robots: why now?

Undoubtedly, for any complex body inhabiting unstructured environments, human or an Embodied robot, the dual problems of shaping motor output during action execution and providing the self with critical information related to feasibility, consequence and understanding of potential actions (of oneself or others) must seamlessly alternate during the evolution of any goal oriented behavior or social interaction. Emerging results from different directions such as functional imaging (Frey and Gerry [39], Grafton [42]), mirror neuron systems (Rizzolatti et al. [80]), language understanding (Pulvermuller [77]), social perspective taking (Koster-Hale and Saxe [57], Gallese and Sinigaglia [41]), tool use and virtual reality (Maravita and Iriki [61], Shokur et al. [83]), now provide converging evidence suggesting that action 'generation, imagery, observation and understanding' consistently engage an overlapping network of cortical areas in the predominantly motor areas of the brain, particularly the parietal-premotor networks (Desmurget and Sirigu [32], Blanke [4]) involved in maintaining an updated multimodal representation of the body and adaptively extended to coupled tools. Ptak et al. [86] review evidence that the dorsal frontoparietal network forms a core system for action emulation used in diverse contexts related to action planning and imagination. Given the diversity of situations *with and without movement* leading to parietal activations, it is absurd to suggest that the parietal areas are specialized in any of these diverse functions (Culham and Kanwisher [19]). It is nevertheless plausible to hint that the underlying processing may be of a more general nature thus deeming recruitment (hence functional recycling) in a wide range of situations. We believe that such a basic function is the ability to simulate the interaction of the body with the environment, the same underlying computations also recycled while coordinating tools or simulating actions of other bodies. Cortical areas involved in functionally representing the body in the brain form the core building blocks of such a computational architecture, to be recycled to find feasible solutions in a multitude of situations that any complex body interacting in an unstructured world (with other bodies) will face. In this context, building up on the Mental Simulation theory (Jeannerod [56]), suggesting that even overt actions are the products of an internal simulation), we posited that both overt and covert actions are the consequences of 'animation' of a 'plastic and configurable' internal representation of the body (human or robot), with the attractor dynamics of force fields induced by the intended goals. This formulation itself is not new and has its roots in the ideas emerging from impedance control (Hogan [50]) and kinematic networks (Mussa-Ivaldi et al. [73]), but nevertheless reformulated both in the context of emerging empirical studies in humans and provides a unified principled computational basis to coordinate/simulate movements of a robot. Such an animation (similar to a puppet coordinated by strings) has various consequences: a) It extends the basic computational idea of EPH from muscles to the body schema; b) offers a low cost solution to coordinate overt movements in highly redundant systems (without explicit inversions or cost function optimization); c) offers a means to recycle the same computational building blocks to engage in covert simulation of movement i.e. to predict the feasibility, consequence, understanding and meaning of 'potential actions' of oneself and other interacting agents. The internal representation of the body i.e. the body schema from the core processing layer to carry out computations related to action simulation/generation. In general, both for a human or a robot, we believe the body schema is *somatotopic* (in accordance with the well-known cortical layout), *action-oriented* (not movement-oriented, action defined henceforth as the animation of the body schema), *multi-referential* (as a synergy generation machine coordinating multiple motor spaces: joints, end effector, tools), plastic, *task-oriented and expandable* (in order to support skill learning and incorporate the internal representation of tools and constraints), *mass-less* (and not involving precise details of muscle activations etc., so as to operate equally in overt and covert conditions where there is no neuromuscular activity), *global but configurable* (in the sense that each action implicitly recruits all the degrees of freedom but configuration is equivalent to a task-dependent pruning). General ideas related to how such an internal representation of the body can be *learnt*, *configured* in a *task specific* fashion, *extended* to coordinated tools and used for both covert simulation and overt execution of movement was described with a range of experiments on the iCub.

4.2. Quest for computational simplicity, configurability and functional recycling

Dexterity in overt movement, purposive behavior with anticipation of the consequences of one's actions, and social intelligence are critical desirable features if robots are to become commonplace assistants in numerous application domains: domestic, industrial, elderly care to mention a few. Prevalent computational modeling approaches generally converge on the role of internal models, but diverge on the perspective of how they might be realized in the brain or modeled computationally (Pickering and Clark [78]). In cognitive robotics, there has been significant interest in the development of internal model based mental imagery and simulation (see Di Nuovo and Cangelosi [27], Schillachi et al. [23] for a review). Such processes have been deployed to enhance performance diverse tasks like visuo-motor coordination (Schillachi [23]), imitation (Demiris and Khandouri [22]), object manipulation using tools (Takahashi et al. [26]), grounding of linguistic labels to body postures (Morse et al. [25]). Simple mobile robots with simulation-based internal models have also been deployed for safety in highly dynamic environments (Blum et al. [24]). While some of the models do not explicitly deal with the issue of body representation, others use diverse formulations like kinematic models, self-organizing maps, Bayesian networks (see Schillachi et al. [23] for a detailed review of various studies in robotics). In this context, our proposal brings back the critical role of body and its internal representation in the brain as a means to both simplify the computational process of coordination of action and at the same time recycle the same mechanism to engage in diverse forward simulations. The proposed body schema networks serve as a "task agnostic" middleware to connect lower level sensorimotor representations to diverse higher level cognitive functions. Consider that the explosive growth in the complexity of the body in a limited number of species is typically concentrated in two body parts (the hand and the vocal tract) that do not have a specific function but are general-purpose tools (for manipulation and communication, respectively) to be employed in infinite numbers of possible manners and purposes. In this sense, given the brain's constraints, critical desirable features for any biologically plausible realization of forward models is *computational simplicity* (to tackle the curse of dimensionality) and goal-specific *configurability* (to ensure flexibility, at the same time reusing/recycling the same hardware as far as possible). In relation to the former aspect, all networks described in this article operate with 'well posed' computations, hence *avoiding the critical need to choose one from many through a computationally expensive optimization process*. In this sense, the forward/inverse models resulting from configured body schema networks has similar computational properties like forward models emerging from predictive coding and active inference (Friston [29], Pickering and Clark [78]).

The degree of analogy between the active inference based approach (Friston [29]) and our body schema based formulation, in spite of numerous formal differences, is apparent if we consider the distinguishing feature of the Active Inference framework as reviewed in [29]: (C1) AI complies with imperatives that apply to all biological systems, (C2) dissolves some hard problems in optimal control, (C3) provides a complete specification of control, (C4) is neurobiologically plausible, and (C5) accounts for action without reference to value. The present article is also answering the same questions: (C1) the notion that movement is a transition from an equilibrium state to another is a rather general feature of all biological organisms; (C2) body schema networks do not suffer the curse of dimensionality as they operate through well posed computations; (C3) hence can be easily scaled up and down according to the task and the environmental interactions; (C4) are equally biologically plausible and biomimetic; (C5) do not require value functions for action generation but may incorporate value functions for action selection and skill learning (Diedrichsen et al. [35]). At the same time, the body schema based formulation is closer to both biomechanics (being an extension to EPH) and the cybernetics of action (to drive goal oriented internal simulation) than the AI formulation. Here, a more general question can be asked as to 'How and Why' computations turn out to be well posed in the proposed computational formulation? The answer is that they are 'constrained' by the physical properties of the system they intend to model i.e. the body. For example, natural direction of causality for a muscle is to receive flow and yield force, and the natural direction of causality for the joint is to receive force and yield flow (which is the reason the joint space receives the force field as input and yields joint rotations as output, which in turn uniquely determines end effector displacement). In fact, a detailed analysis of issues related to modularity and causality in physical system modeling goes back to a seminal paper by Hogan [50], with contributions from Henry Paynter (i.e. the Bond graph approach, Paynter [75]), that we exploit in our computational architecture.

4.3. Ongoing extensions: connecting the body-schema to a dynamic processor

While experiments in this article particularly focused on coordinating the upper body of iCub, an ongoing extension to the computational architecture is related to whole body coordination: with coupled loads that alter both the kinematics and dynamics during coordination. In general, physically-coupled load is a ubiquitous constraint on any human action as well as robotic plant dynamics: Consider that, humans often wear and carry items during manipulative tool use (sometimes even under greater visual and aural encapsulation for protection like fire fighters, soldiers).

The same applies to both industrial robots that wield and transport different tools and items as part of their tasks (e.g. car manufacturing and robotic surgery devices). While most humans wear some form of personal protective equipment (PPE; heavy footwear, rain jackets) or carry loads (book bags), the particular interest in PPE is for those in critical situations (fire fighters, soldiers) who often wear loads in excess of 40% body weight and who need to pick-up information for prospective control of action in dangerous environments. In these critical situations, the investigation into the constraints of PPE and its consequences on 'perception–action–cognition' loop is critical to foster enhanced 'survivability', 'self-protection' and success in 'realization of task goals'. First simulation results in this context are summarized in a recent article (Morasso et al. [70]). This has resulted in the development of a software package *PeterPan* that incorporates (1) the configurable body schema described in the previous section; (2) a biomechanical simulator of whole-body dynamics based on OpenSim and Simbody softwares; (3) a set of neuromuscular controllers for the different DoFs; (4) a software middleware YARP for integrating in a robust way the multimodal streams of information related to the whole body simulation. The hope is that this direction of activity can potentially provide greater insights into: a) the functional capability and survivability of people wearing different kinds of personal protective equipments (PPE) while performing their day to day tasks; b) use this knowledge to redistribute loading of their bodies in an optimal fashion; c) create ergonomic designs of PPE's, safety gears etc. worn by people who are expected to perform precision tasks in critical conditions (like soldiers, fire fighters among others).

4.4. Connecting the body to inanimate tools and other animate agents

The argument of configurability and recycling is interesting because it can be extended to coordinated tools and other bodies. As demonstrated by Iriki and Sakura [53], with practice a rake becomes a part of the acting monkey body schema. Recording from monkeys trained to use pliers to grasp otherwise unreachable food rewards, Umiltà et al. [89] demonstrated that the end effect of learning skilled tool use was the transfer of the temporal discharge patterns that control 'hand grasping' (area F5) to the tool, as if the tool was the hand of the monkey and its tips were the monkey's fingers. The body schema based PMP framework closely resonates with these results. The tool space is represented exactly in the same manner as any other intrinsic motor space. And during coordination, the body and the tool act as one cohesive unit to realize a goal at hand or afford mental simulations related to ensuing consequences of possible use of the tool itself (Fig. 1D, Fig. 5). An intriguing idea proposed by Iriki [53] is that the ability to literally incorporate external objects into one's own body schema and the ability to 'objectify' other bodies, thus recycling the same neural machinery, are two sides of the same coin. The consequence is quite remarkable. As soon as one's own body becomes objectified and separate, one must assume a subject with an independent status that is orchestrating the movements of both the body and its tools. In this way, the 'mind' could emerge naturally as a sort of 'virtual concept', a placeholder for the link between the 'subject' and the 'objects' of manipulation, which includes the body itself (and other bodies). There is already some evidence in this regards. It has been shown that significant intracortical connections between the intraparietal cortex (IPS) and the temporo-parietal junction (TPJ) can be forged by tool-use training in adult monkeys (Hihara et al. [51]). In human subjects, activation of the homologous circuitry at the temporo-parietal junction is detected in self-objectification paradigms (Corradi-Dell'Acqua et al. [20], Blanke [4]). Harnessing this basic concept of extension of body (body schema) to coupled tools, virtual avatars, neuroprosthetic limbs, recent developments in virtual reality and neuroprosthetics are opening novel avenues for human enhancement of sensorimotor and cognitive function. In the field of social cognition, now there is growing consensus that that when interpreting others actions, people recruit motor representations as if they were themselves acting (Gallese and Sinigaglia [41], Gallese and Cuccio [40]). Simply put, understanding may be conceived as an internal simulation that entails the reuse of our own ability to act with our bodily resources in order to functionally attribute meaning to 'others' actions, recycling some of the same cortical substrates the enable us to act ourselves. A 'configurable, plastic' internal model of the body serves as a fundamental computational layer to facilitate such inferences.

In sum, overt movements are just the tip of the iceberg, under the surface is hidden a vast territory of actions 'without movements', decoding their neural/computational basis is the essence of motor cognition. The goal specific animation of a 'plastic, configurable' body schema to both simulate, generate actions is one perspective in this direction, grounded on the biomechanics of the body (as an extension to EPH) and connected to emerging trends in motor neurosciences.

Acknowledgements

This research presented in this article is supported by the European Union through FP7 project DARWIN (Grant No. FP7-270138), and U.S. Department of Defense through the project "Consequences of Loading on Postural-Focal Dynamics" grant no. W911QY-12-C-0078. A software implementation of the PMP framework along with a user manual describing installation and use of the software is made available open source at https://svn.code.sf.net/p/robotcub/code/trunk/iCub/contrib/src/morphoGen/ under the GNU General Public License. We thank the reviewers for their time and constructive feedback to revise the draft manuscript.

Appendix A. Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.plrev.2018.04.005.

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