What does learning to 'draw a circle' have to do with driving, cycling, unwinding and screwing?

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Can a baby humanoid learning to draw a circle, at the same time also learn about the abstract notion of 'Circularity'? Common actions like controlling a steering wheel, uncorking, unwinding, screwing, cycling among others also result in formation of circular movements of different scale, in different coordinate frames, created by different body or tool effectors, causing different environmental consequences, thereby serving different purposes. Similarly, the common denominator in drawing a line, pushing a ball with a stick, pulling an unreachable object closer to oneself with a rake etc is the notion of 'Straightness'. Undoubtedly, trajectory formation is one of the central functions of the neuromotor controller. Common day to day actions result in formation of spatiotemporal trajectories of different degrees of complexity. Given the diverse range of skilled actions we command effortlessly, it is intriguing to investigate if there is an underlying order/invariance that allows the motor system to systematically 'compose and reuse' motor knowledge during the synthesis of purposeful movement. In other words, is there a small set of abstract motor vocabulary that when combined, sequenced, and shaped to 'context', allows the emergence of the staggering flexibility, dexterity and range that human actions possess? In this article, we present the design of a hierarchical action generation/learning system for the iCub humanoid that incorporates some crucial properties that could lead to a plausible answer to the above question. We demonstrate the value of the architecture using an example of how motor knowledge acquired by iCub while learning to draw (skill 1) can be systematically recycled in a task of learning to bimanually control a toy crane as a tool to reach otherwise unreachable objects in the environment (skill 2). We believe the underlying mechanism is quite general and can be applied to acquire a wide range of skilled actions in a similar manner. With the help of Figure 1 that shows the central building blocks and high level information flows in our architecture, we outline some crucial/novel features that we believe are fundamental for constructing a growing motor vocabulary in acting/learning robots.

1) *Learning through Imitation, Exploration and Motor Imagery:* Three streams of learning i.e. learning through teachers demonstration (information flow shown in black arrow), learning through physical interactions (blue arrow) and learning through motor imagery (loop 1-5 shown in black arrow with red outline) are integrated into the architecture. All the three streams are employed while learning the two skills (drawing and crane toy) presented in this article.

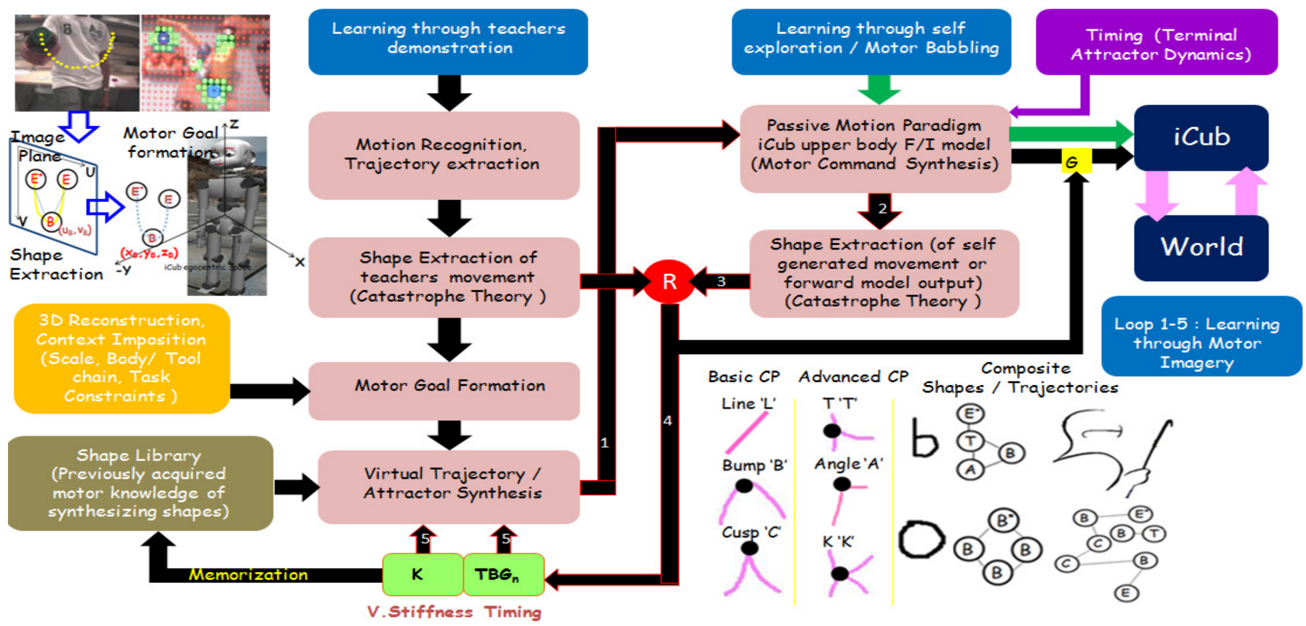
2) *From Trajectory to 'Shape, towards 'Goal Independent' motor knowledge:* Most skilled actions involve synthesis of spatio-temporal trajectories of varying complexity. A crucial feature in our architecture is the introduction of the notion 'Shape' in the motor domain. A trajectory may be thought as a sequence of points in space, from a starting position to the ending position. 'Shape' is more abstract description of a trajectory, which captures the essential information or critical events in it. By extracting the 'shape' of a trajectory, it is possible make it 'context independent' i.e. liberate the trajectory from the details of scale, location, orientation, purpose and body effectors that underlies its creation. Using Catastrophe theory [1], [2] have derived a set of 12 primitive shape critical points (CP) sufficient to describe any trajectory/line diagram in general. Using this system it is possible to move from visual observation of the end effector trajectory of the teacher to its shape. For example, the essence of a trajectory like 'U' is the presence of a minima (or Bump 'B') in between two end points ('E'), hence represented as E-B-E. A circle is a composition of 4 bumps and so on. From the action generation perspective, in a recent work we have shown how it is possible to teach iCub to generate all the shape CP's derived in [6,7], through the virtual trajectory generation system (VTGS).

3) *Imposing context, towards 'Goal Dependent' motor action:* Since 'shape' is conserved during coordinate transformation, scaling or the end effector employed, it gives iCub the capability to generate a wide range of movement trajectories based on the context. So when iCub draws a curve like 'C' with a paint brush or bimanually maneuvers the steering wheel of the crane toy, both result in trajectories that result in same shape representations (in this case, curves of type 'E-B-E'). Since the knowledge to generate these shapes have already been learnt while drawing, the VTGS can just collect the information from the shape library, scale it to context and generate the virtual trajectory to maneuver the crane toy like the teacher (). Same is the case with actions like screwing, unwinding, cycling etc that also result in same shape representations in different context, serving different utilities, for which the motor knowledge of shape synthesis can be reused.

4) *From virtual trajectory to Motor Commands: Linking redundancy to Task dynamics, Timing & synchronization:* The virtual trajectory synthesized by the VTGS is coupled to the appropriate internal body (body + tool) model to now synthesize the motor commands taking into account task dynamics. The Passive Motion Paradigm based forward inverse model for iCub upper body is used in this phase for action generation [3-5]. The interaction between PMP and VTGS is similar to the coordination of the movement of a puppet by a puppeteer. As the virtual trajectory pulls the relevant end effector in a specific fashion, the rest of the

body (arm and waist joints) elastically reconfigures to allow the end effector to track the evolving virtual trajectory. When motor commands synthesized by this process of passive relaxation is actively fed to the robot, it reproduces the movement, hence generating the motor action. The shape of the self generated movement or forward model output (once again computed through CT) allows a comparison to be made with the 'shape' of the teachers movement to close the monitoring loop during learning. Gradually moving from the visual observation of teachers trajectory to its shape, collecting knowledge to generate that shape from the shape library (in this case acquired while learning to draw), synthesizing a virtual trajectory fitted to context, coupling the virtual trajectory to both arms (using PMP), iCub is able to swiftly maneuver the crane toy like the teacher demonstrated. From its own actions with the tool, it then learns the 'tool jacobian' i.e change in the magnetized tool tip position of the crane toy as a result of the change in its end effector position. The tool jacobians when coupled with the jacobians of the upper body using PMP allows iCub to maneuver the crane toy in a goal directed fashion. In this way motor knowledge acquired while learning the drawing skills can be systematically reused by iCub to swiftly learn to steer the crane toy in a goal directed fashion.

Figure 1. Central building blocks and high level information flows in the hierarchical action learning/generation system for iCub. Top left panel



shows the stages of trajectory extraction, shape extraction and 3D reconstruction in iCub's egocentric space. Bottom right panel shows 6 primitive shape critical points iCub both visually recognized and generated by iCub. Shape representations of complex trajectories can be decomposed into combinations of these critical points.

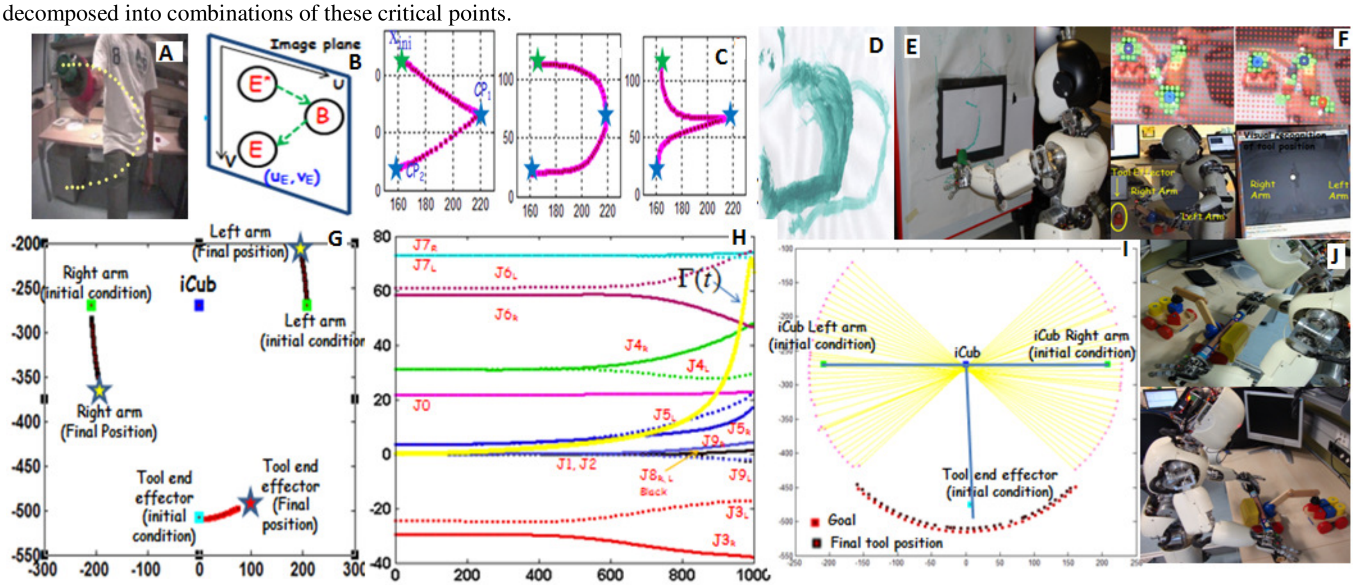


Figure 2. Panels A-E shows iCub learning to draw a trajectory of shape 'E-B-E' on the drawing board. Panel F shows the scenario where a trajectory performed of similar 'shape' but different context is performed by the teacher while bimanually steering the crane toy. Panel G shows the trajectories of the two end effectors and the resulting trajectory of the tool tip when iCub imitates one such trial, using the knowledge of synthesizing similar shapes acquired by it previously while learning to draw. Panel H shows the evolution of motor commands synthesized by PMP in the 17 Degrees of freedom intrinsic space (joints and waist) (J0-J2: Waist, J3R-J9R : Right Arm and J3L-J9L: left arm) while

generating the trajectories of panel G to steer the crane toy. These experiences are used to learn the tool jacobian that maps the relative position of the end effectors to its consequence i.e corresponding position of the tool effector. Once tool jacobian is learnt the tool can be added as an additional component in the PMP chain to coordinate goal directed body + tool movements. Panel I shows shows results of 100 reaching trials to different goal targets realized by iCub by coordinating the toy crane bimanually. Panel J shows two snapshots of iCub using the crane toy to reach otherwise unreachable goal targets.

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