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

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I. INTRODUCTION

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 diversity of human actions? The answer to the above question is important 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. The imitation loop initiates with the teachers demonstration and ends with iCub reproducing the observed action. The motor imagery loop is a sub part of the imitation loop, the only difference being that the motor commands synthesized by the passive motion paradigm [4-5] based forward/inverse model is not transmitted to the actuators. This loop hence allows iCub to internally simulate a range of motor actions and only execute the ones that have high performance score ‘R’. 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 spatiotemporal 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 only 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 the shape of 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 more abstract ‘shape’ representation. For example, the essence of a trajectory like ‘U’ is the presence of a minima (or Bump ‘B’ critical point) in between two end points (‘E’). Hence the shape is represented as graph ‘E-B-E’. If the ‘U’ was drawn on a paper with a pen or if a boy runs a ‘U’ in a playground, the shape representation does not change. A circle is a composition of 4 bumps and so on. While this is ‘perceptual’, our goal was to achieve the inverse of this operation, i.e. teach a humanoid robot to synthesize these primitive shape critical points, and hence enable to learn the grammar to generate a wide gamut of trajectories in different contexts. 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].

3) Imposing context, towards Goal Dependent’ motor action: Since ‘shape’ is conserved during coordinate transformation, scaling or the end effector employed, acquiring the motor knowledge of synthesizing shapes 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
4) Virtual Trajectories: Decoupling ‘Action’ from the ‘Actor’:

Virtual trajectories can be ‘decomposed’ into combinations of primitive shape CP’s using CT, inversely can the motor actions needed to create them be ‘composed’ using combinations of the corresponding ‘learnt’ primitive actions. Rather, that they act as an attractors to the internal (body+ tool) model involved in action generation and play a crucial role in deriving the motor commands needed to create the shape.

5) 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 are actively fed to the robot, it reproduces the movement, hence generating the motor action. When the teacher demonstrates iCub to bimanually steer the crane toy (figure 2, Panel F-J), by 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.

2. CONCLUSION

A wide range of human actions result in formation of trajectories that ultimately result in similar ‘shape’ representations. Most important among them are line, bump and cusp critical points described in [1-2]. For example, drawing a circle, driving a steering wheel, uncorking, winding, cycling, stirring etc are actions that have ‘circularity’ as invariant in them. If we teach a humanoid robot to synthesize ‘Shapes’ [6], we can endow then with the powerful capability to ‘compose, recycle’ the previously acquired motor knowledge to swiftly learn wide range of other motor skills. Is ‘shape’ the invariant through which humans imitate/mime effortlessly and instantaneously? Future research in this direction will be aimed at answering/validating these questions.
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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REFERENCES