Learning to draw after observing a teacher: iCub's scribbles and shapes

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Trajectory formation is one of the basic functions of the neuromotor controller. Reaching, avoiding, controlling impacts, drawing, dancing and imitating are common motion paradigms that result in formation of spatiotemporal trajectories of different degrees of complexity. Transferring some of these skills to humanoids not only enhances their 'mobile intelligence' but also helps understanding how we ourselves learn, store, compose and generalize motor behavior (to new contexts). This paper presents our ongoing attempts to teach baby humanoid iCub to draw line diagrams, write English alphabets and make some simple sketches after visually observing a teachers demonstration. The playful scenario encompasses three central objectives: 1) Achieving a gradual progression in iCub's artwork starting from scribbles, learning some basics, combining and exploiting this motor knowledge to create more complex, composite motor behavior; 2) Derive a minimal set of computational transformations necessary to swiftly transform the visual observation of teachers action to motor commands of the student and 3) Integrating three crucial streams of learning i.e motor babbling (self exploration), imitative action learning (social interaction) and mental practice (and self evaluation) to give rise to motor knowledge endowed with a level of compositionality, generalizibility and body effector/task independence. A crucial feature in the proposed framework is also that, what iCub learns to emulate is not the teachers 'end effector trajectories' but rather their 'shapes'. The resulting advantages are numerous. The extracted 'Shape' being a high level representation of the teachers movement, endows the learnt action natural invariance wrt scale, location, orientation and body end effector used in its creation (ex. it becomes possible to draw a circle on a piece of paper or run a circle in a football field based on the internal body model to which the learnt attractor/virtual trajectory is coupled).

The central building blocks/transformations in the proposed framework for teaching iCub to draw are shown in figure 1. As seen, the stimulus to begin with is the teacher's demonstration, usually composed of a sequence of strokes, each stroke tracing a finite, continuous line segment inside the visual workspace of both cameras. The captured video of the demonstration undergoes a preprocessing phase that extracts the trajectory traced by the teacher (as observed in camera plane coordinates). The next step is to extract an abstract high level representation of this trajectory, i.e its 'shape' using the framework of Catastrophe theory [1-3]. The central idea in the CT framework is that the global shape of a smooth function f(x) can be fully characterized by a set of special local features (like peaks, valleys etc) called *'critical points'* (henceforth CP) where first and probably some higher order derivatives vanish. Further developing CT, [4] have shown that 12 CP's (shown in figure 1)are sufficient to characterize the shape of any line diagram, namely: Interior Point, End Point, Bump (i.e maxima or minima), Cusp, Dot, Cross, Star, Angle, Wiggle, T and Peck. For example the essence of the shape 'U' is the presence of a bump or a maxima somewhere in the center, the shape '0' is composition of a maxima and minima and so on. We call this minimal (and context independent) representation as the *'abstract visual program (AVP)'*.

AVP may be thought as a high level visual goal created in iCub's brain after perceiving the teachers demonstration. To facilitate action generation to take place, this visual goal must be transformed into an appropriate *motor goal* in iCub's egocentric space. To achieve this, we have to transform location of the shape critical points computed in the image planes of the two cameras into corresponding critical points in the iCub's egocentric space (x,y,z) by a process of 3D reconstruction. In addition, task specific constraints like scaling/ amplification during shape synthesis, kinematic chain/ body DoF involved in the action generation, kinematic model of tool etc are specified at this point, hence transforming the AVP into a Concrete motor goal (CMG) for iCub to reproduce. *Formation of CMG is the first step in the action generation process. As seen in figure 1, the* CMG basically consists of a discrete set of *shape* critical points (their location in iCub's ego centric space and type), that describe in abstract terms the 'shape' iCub must now *learn to draw*. For example, the CMG of the shape 'U' (figure 3) has three CP's (2 end points 'E', and one bump 'B' in between them). Given any two points in space, an infinite number of trajectories can be shaped passing through them. How can iCub learn to synthesize a continuous trajectory similar to the demonstrated shape using a discrete set of critical points in the CMG? This problem is solved using two subsystems: Virtual trajectory generation system that deals with the problem of transforming a *discrete sequence of shape critical points into a continuous sequence of equilibrium points*.

For the simple case of 2 CP's (as in the example of synthesizing a shape 'U'), VTGS is a dynamical system described by $\dot{x}_T = K_1\gamma_1(t)(x_{T1} - x_T) + K_2\gamma_2(t)(x_{T2} - x_T)$ where X_{T1} and X_{T2} are the spatial locations of the CP's, K defines the virtual stiffness (see figure 1) and ϒ implements the terminal attractor dynamics [9].

The basic idea in the VTGS system is that by pseudo randomly exploring the space of K and the overlap between time base generators ϒ, different trajectories through the CP's can be synthesized. Further, the amount of exploration is constrained by the fact that once iCub learns to draw the 12 shape CP's derived using CT, any line diagram can be expressed as a composition of these primitive shape features. Further, the 12 primitive shape critical points are themselves compositions of straight lines, bumps and cusps, all of which can be synthesized by exploring the space of K from 1-10. Once iCub learns to draw lines, bumps and cusps, rest of the shapes can be created through composition. *Hence the central idea is that since more complex shapes can be 'decomposed' into combinations of these primitive shape CP's, inversely the actions needed to synthesize them can 'composed' using combinations of the corresponding 'learnt' primitive actions.* Maximum effort in terms of motor exploration is applied to during the initial phases to learn the basics (drawing the primitives). During the synthesis of more complex shapes, composition and refinement of previous knowledge takes the front stage, exploration being reduced to a handful of mental trials. We must finally remark that the virtual trajectories synthesized in this fashion are not really shapes. Rather, they have a higher cognitive meaning, in our dynamic modeling framework, in the sense that they act as attractors to the internal body+tool model involved in action generation and play a significant role in deriving the motor commands needed to create the shape itself. The Passive Motion Paradigm [6-8] based forward/inverse model for iCub upper body coordination is used for the motor command synthesis. The interaction between the virtual trajectory and the PMP system is analogous to the coordination of a puppet by a puppeteer (virtual trajectory serving as a moving point attractor to the PMP system). The final step is to generate a score of performance of how closely the shape drawn by iCub matches the demonstration. This is easily done by performing a Catastrophe theory analysis on the self generated movement (forward model output) to extract the shape of the self generated movement. We call it as Abstract Motor Program (AMP) that can be directly compared with AVP to close the loop. Since PMP is essentially a forward inverse model, the sequence of exploration in the space of K, virtual trajectory generation, motor command generation, end effector trajectory prediction through forward model, AMP extraction and evaluation can be done virtually in the mental space of iCub. The solutions with high score are then physically created by iCub on a drawing board placed about 35 cms in front of it, using a paint brush of 12cms length that is integrated into the PMP model. *Hence part of the learning is acquired by observing the teacher, part through self exploration in the space of virtual stiffness and timing, and part through mental rehearsal in the VTGS-PMP loop.* Figure 2 presents some experimental results of the progress of baby humanoid iCub in its artwork beginning with primitive shapes like Bump, Cusp, then moving to more composite ones like 'S' and recently a simple sketch of 'Gandhi'. Finally, teaching iCub to draw opens new avenues for iCub to both gradually build its mental concepts of things (a star, house, moon, face etc) and begin to communicate with the human partner in one of the most predominant ways humans communicate i.e. by writing.

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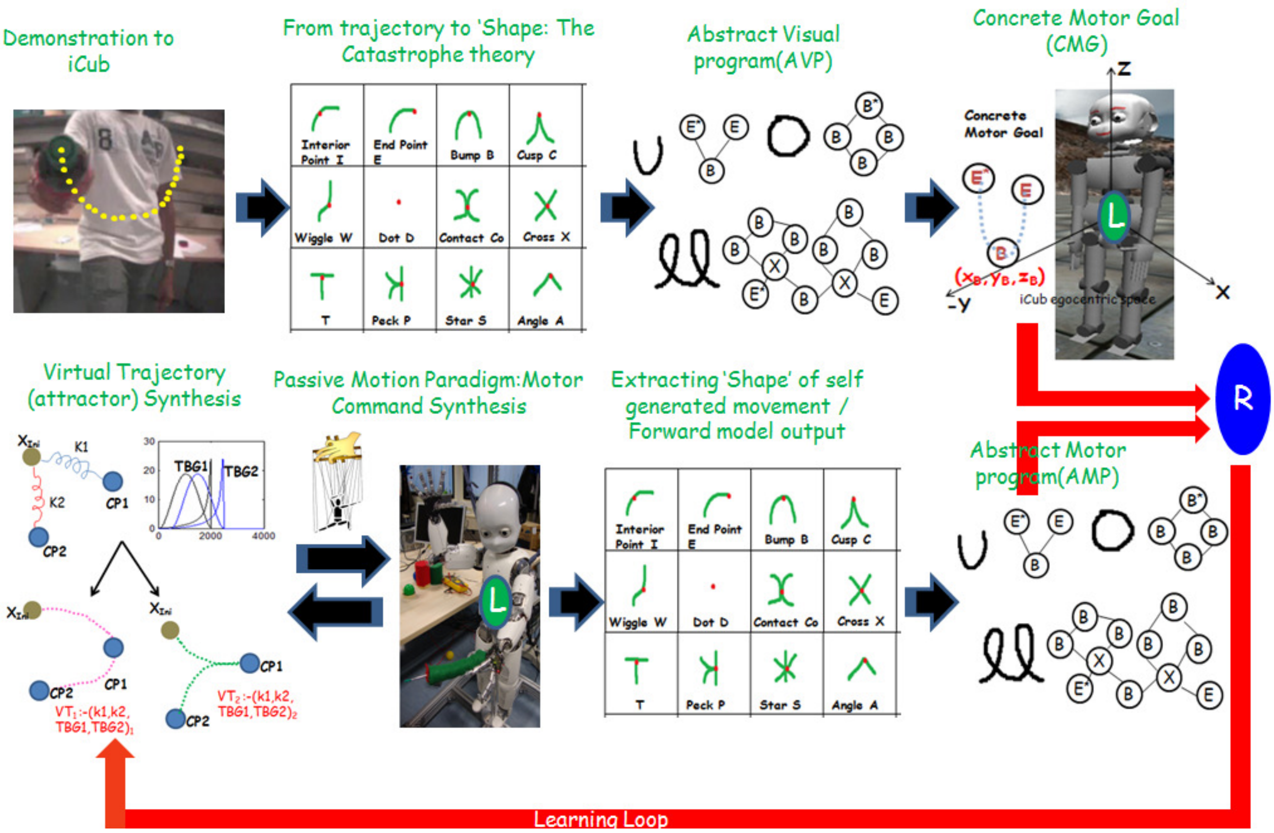

Figure1 shows the overall information flow in the proposed system, beginning with the demonstration to iCub (for example a 'U'). This is followed by an analysis of the critical points in the shape using Catastrophe theory that leads to the creation of an abstract visual program. The context independent AVP is now transformed into a concrete motor goal by applying relevant task specific contexts. CMG forms the input of the VTGS system that synthesizes different virtual trajectories by pseudo randomly exploring the space of stiffness (K) and timing (TBG). The VT is now coupled to the relevant internal model (PMP) to derive the motor commands. Analysis of the self generated movement (i.e output of the forward model) using CT now extracts the Abstract motor program that is compared with the AVP, to self evaluate a score of performance. A reinforcement loop follows.

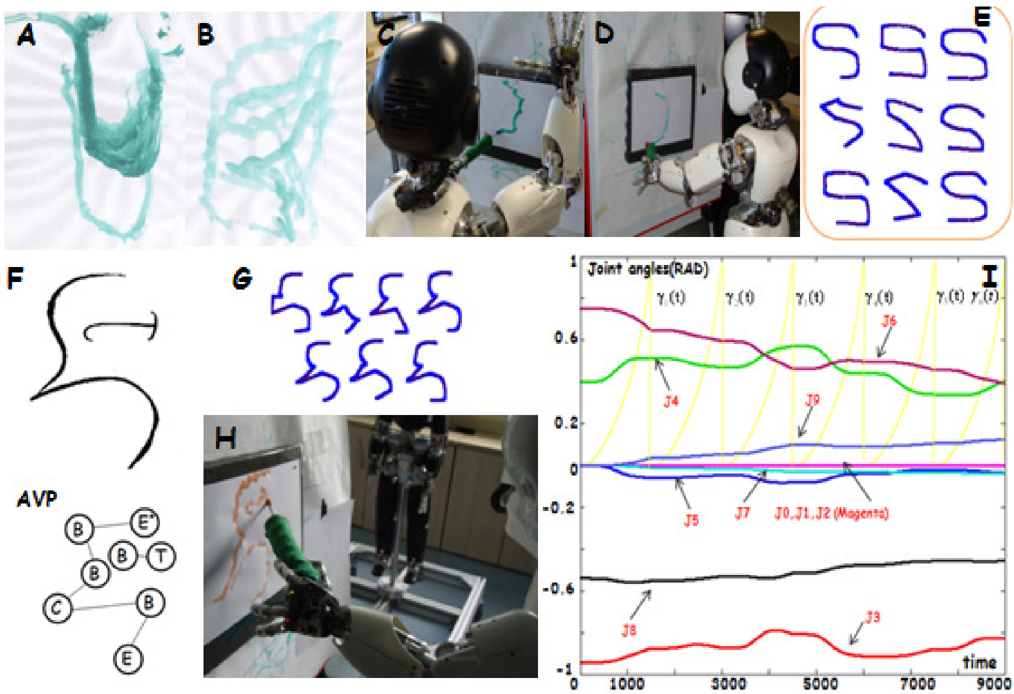

Figure 2. Assortment of experimental results while teaching iCub to draw. Panels A-D show sketches made by iCub while learning to draw primitive shape features like bumps and cusps. Panel E shows the sequence of 9 shapes traced by iCub with a goal to draw 'S', during learning iterations consisting of small random titillations around the range virtual stiffness values learnt previously for drawing bumps. Panel F shows the another goal : Gandhi sketch and its AVP. Panel G shows a 7 different predicted forward model outputs (end effector trajectories) during iCubs mental attempts to draw it. Panel H shows the final solution of Gandhi Sketch.

Panel I: iCub's left arm-waist chain is used for Action generation using PMP. The trajectories of motor commands synthesized at the intrinsic space using PMP while drawing the Gandhi Sketch (the single stroke outer shape) are shown in panel H. The TBG functions γ are also shown (in yellow). As seen, the complete motor command set buffered to the actuators is a matrix of 9000 rows (iterations in time) each having 10 columns (values of the 10 Degrees of Freedom in the left arm-torso network, at each time instance).