Body Schema Modelled as a Collection of Manifolds

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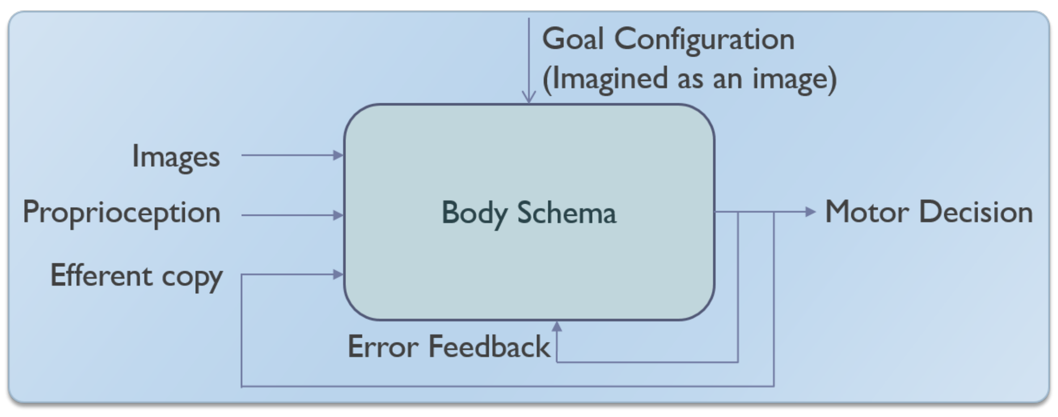
Body Schema

- Part of the space which is within the reach of a cognitive agent is its **peripersonal space**, and the rest is **extrapersonal space**.
- **Body schema** is a sensorimotor representation of the agent's body and its peripersonal space in its brain.
- Allows the agent **to infer the position and orientation of its limbs and of the objects in its peripersonal space**, relative to its world.
- Enables the agent **to perform actions** in its peripersonal space.

An Empiricist View of Body Schema

- **Nativism vs. Empiricism**: Other animals (e.g. monkeys and cows) have **innate** motor skills, but in humans most of the motor skills are **learnt**.

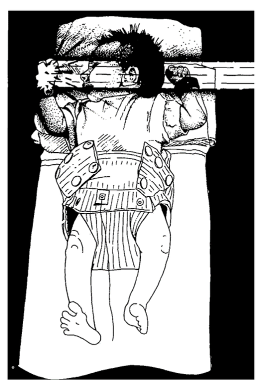


Previous Works on Body Schema

- **In biological systems**, body image and body schema are modelled as self-organizing maps.
- **In robotic systems**, body schema is modelled as kinematic chains, self-organizing maps and Bayesian networks.
- A survey on various models of body schema can be found in [HMA+10], with an emphasis on body schema for robotic systems.
- Each of these models focuses on one key issue of body image or body schema and does not address other issues. Some of them assume knowledge about the agent's body. [HS04, HFO+08, SPB09, MCLM10]

A Developmental Observation

- Human infants move and observe their limbs from the age of 10 to 24 days. [vdM97].
- Start **swatting** at the age of around **6 weeks** and start **reaching** at around the age of **12-20 weeks**. [TCK+93]
- Hand-eye coordination and visuo-motor learning happens during these phases.
- Vision and touch play a crucial role in learning to use the body.



Source: van der Meer [vdM97]

Dimensionality Reduction

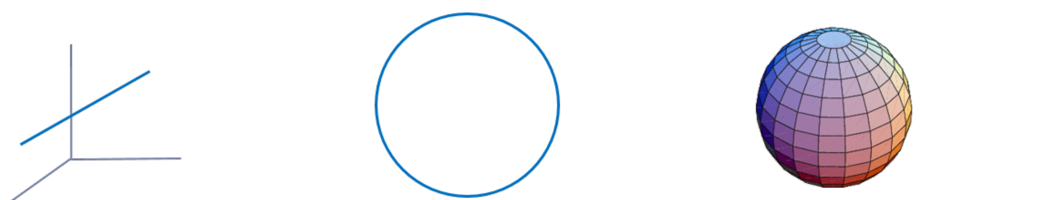
- The **visual and proprioceptive input** that the brain receives **are very high-dimensional**.
- But the body motions have very **few degrees of freedom**.
- Hence the set of images of all possible body motions lies on a much **lower dimensional subspace** of the raw input image space.
- Discovering the underlying low-dimensional subspace, called a **manifold**, for a given set of input points is called **dimensionality reduction** or **manifold learning**.

This Work

- Proposes a **computational model of body schema** based on manifolds.
- Suggests how it can be **acquired** just by observing one's own body without requiring any other knowledge.
- Suggests how it can be **updated** as the body grows?
- Demonstrates how it could be used for
  - **Moving to a desired pose**
  - **Swatting and reaching of objects** within peripersonal space
  - **Avoiding obstacles and planning motions**

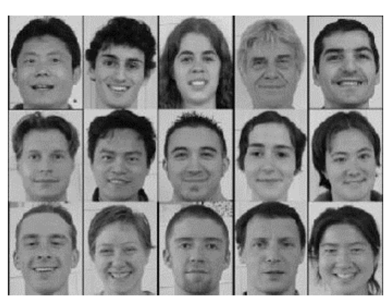
Manifold: Intuitions and Examples

- **How many parameters** are needed to describe a system?
- **On a small-scale, what does the object look like**?



Line in $\mathbb{R}^3$: 1-D   Circle in $\mathbb{R}^2$: 1-D   Surface of sphere: 2-D, Solid sphere: 3-D

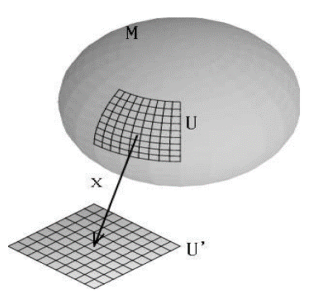
- **What is the probability** that a 100×100 greyscale pixel grid looks like a human face, when the pixel intensities are chosen randomly?
- **How many degrees of freedom** - number of independent directions at any given point, while still remaining on the subspace?



Courtesy: CDSST Eigenfaces

Manifold Definition

- **Informal**: A d-dimensional manifold is a probably nonlinear space which locally resembles a patch of $\mathbb{R}^d$.
- **Formal**: A d-dimensional topological manifold M is a Hausdorff topological space, with a countable basis for the topology, which is locally homeomorphic to $\mathbb{R}^d$. For every point $p \in M$, there is an open neighborhood U containing p, an open set $U' \subset \mathbb{R}^d$ and a homeomorphism $x : U \to U'$.

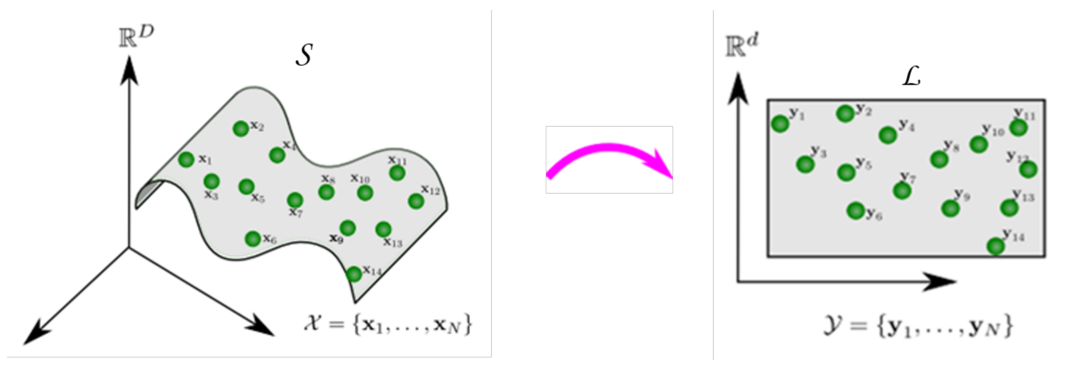


Source: Differential Topology. Notes by Bjorn Ian Dundas

Manifold Learning

(Also known as **Non-linear Dimensionality Reduction**)

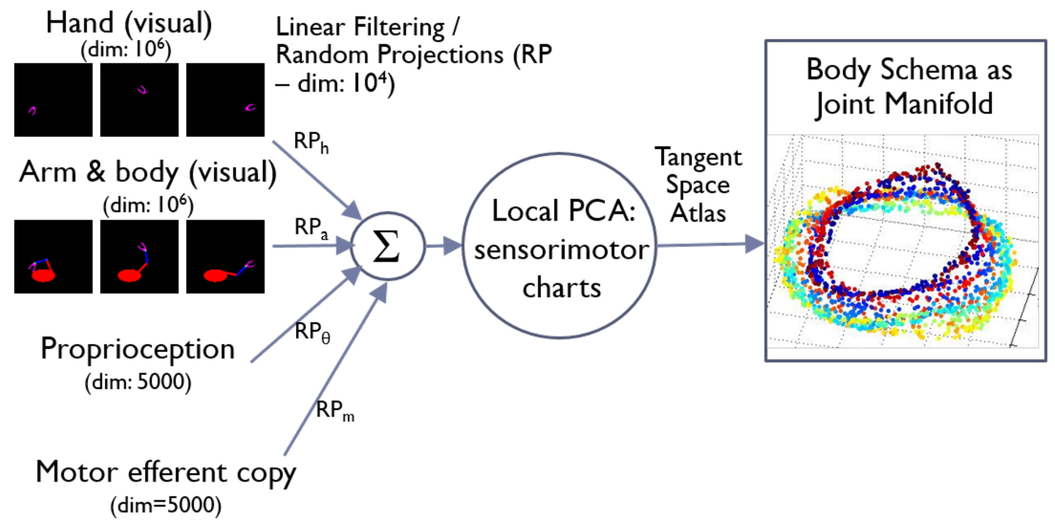
- Given a finite set of points: $X \in R^{D \times N}$ drawn from a manifold;
- Learn a low dimensional representation $Y \in R^{d \times N}$ of X, such that $d << D$ and $x = f(y) + \epsilon$, where f is the non-linear function that generated X from a latent parameter space.
- Ex: Isomap, LLE, MVU, Deep Auto-encoder, LTSA, hLLE, Laplacian Eigenmaps. [Bur09]



Source: Manifold Learning: Practical Difficulties and Current Solutions; Tutorial by Diana Mateus, September 2011

Body Schema and Manifold Fusion

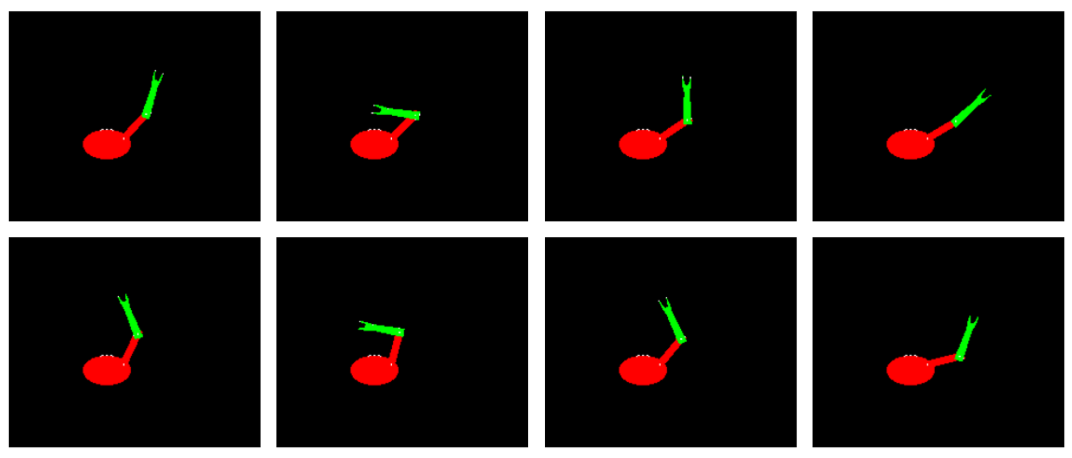
- Motions of each limb of the body form a manifold of the same dimension as the degrees of freedom of that limb.
- **A collection of all these manifolds constitutes the body schema.**
- An action involving one or more limbs of the body corresponds to a path on the joint manifold of the composite limb motions.
- Different sensory modalities can be fused together using random projections [GS12] to form a joint manifold.



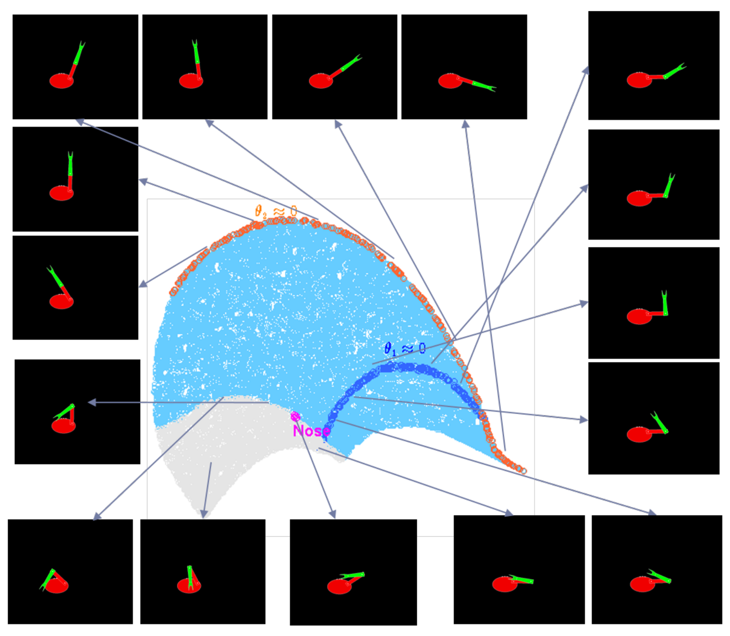
A Computational Model for Body Schema

The following procedure results in a discrete approximation of the motion manifold.

- **Collect images of** the agent in a set of N **random poses**.

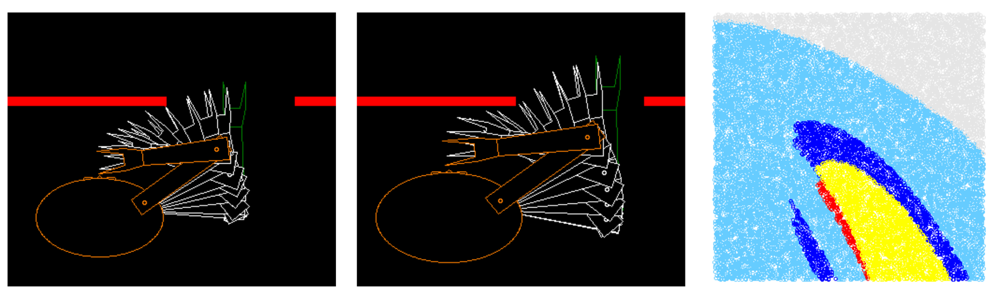


- **Construct a neighbourhood graph** G on the image space using some image metric. Each node of G corresponds to a pose of the agent.
- **Objects in the peripersonal space** correspond to the nodes of G for which the corresponding poses touch/hit the object.
- A **motion between two poses corresponds to a shortest path on** G and an **action is a series of motions**.

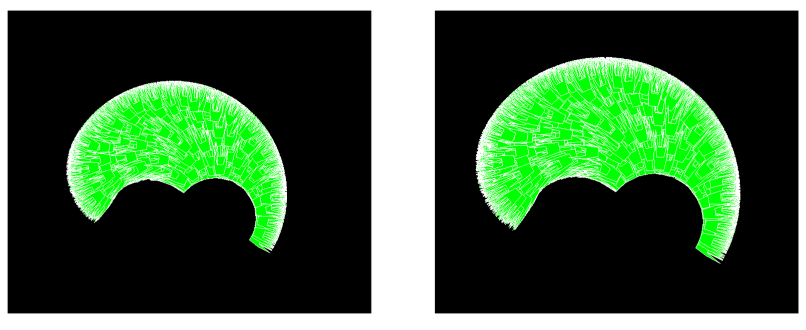


Growing Body

- Body growth is fairly gradual; body schema (i.e, the neighbourhood graph G) can be updated at regular intervals, to adjust for the changes in the obstacle map.
- Path between a pair of poses of the agent in its infancy and after some growth. Here the hand is moving from a random pose to reach the mouth area through a window (gap in the red bar) in its work space.

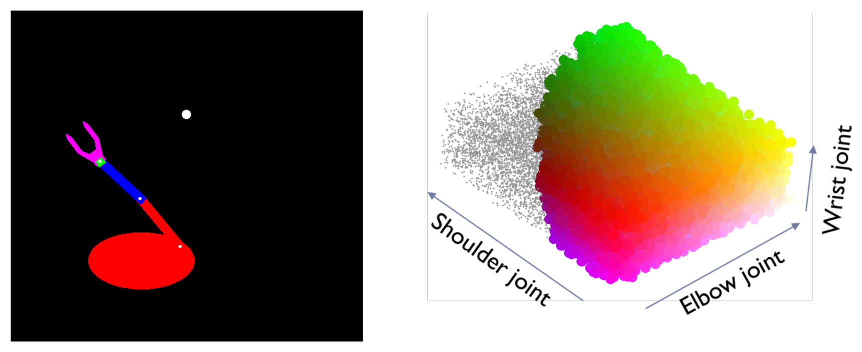


- Obstacle region marked on the angle space: yellow - common obstacle area at the two ages; red - obstacle for just the infant robot; blue - obstacle for just the bigger robot.
- The peripersonal space at infancy and after some growth:



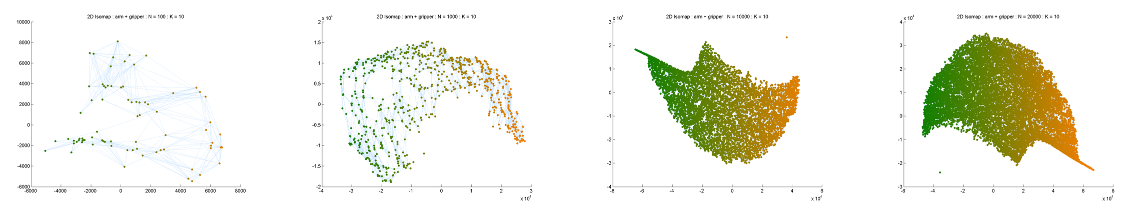
Another Example

- A simulated arm with 3 links moving in the horizontal plane
- Its body schema using proprioceptive inputs (random projections of joint angles), with the torso region marked in grey

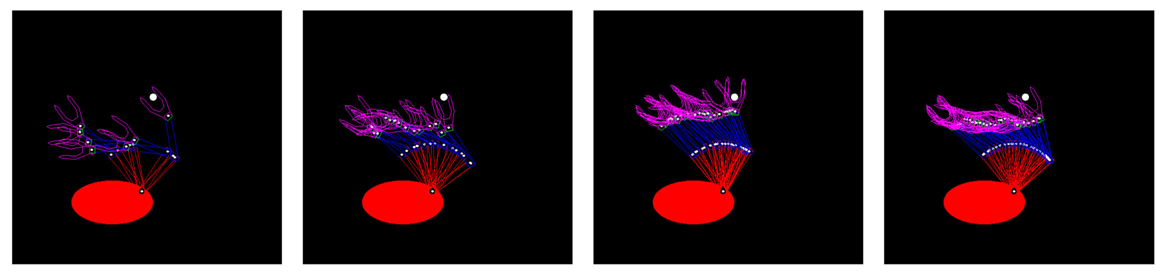


Swatting and Reaching

- Graphs used for motion planning. Number of nodes = 100, 1000, 10000, 20000 respectively.
- Each node in the graph represents a random trial by the agent to reach the object. More nodes means more experience.



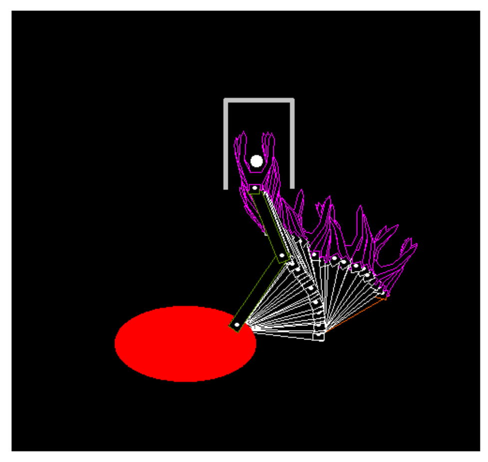
- Trajectories followed by the agent in the workspace to swat the object:



- **Swatting getting better with experience.**

Planning Motions for Actions

- Actions are series of motions modeled as geodesic paths on the body schema manifold, which are approximated by shortest paths on the neighbourhood graph.
- The 3-dof agent tries to grasp an toy from inside a box.



Conclusions

- We showed how body schema can be computationally modelled, acquired based on visual input alone, updated as the body grows and used for performing actions in the peripersonal space.
- We plan to do the following in future:
  - Incorporate tactile feedback in to the current model.
  - Address how the model changes with tool use.

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Acknowledgement

This work was supported by the Research-I Foundation.

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