# Novel Representations for Sensorimotor Learning for an Artificial Body Schema on Humanoid Robots

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In robotics, the term *body schema* refers to adaptive representations of a robot's own body and involved sensorimotor relations. Such representations are obtained by machine learning, ideally, autonomously from self-observation. The body schema grants robots much higher degrees of autonomy as it allows the compensation of changes to the body (for instance, those induced by holding a tool) without the need of manually created explicit models.
In our work, we focus on sensorimotor learning, which is an important (or arguably the most important) aspect of the body schema. Sensorimotor learning creates models that link signals from various sensors of the robot (for instance, proprioception and vision) and motor control signals together and thereby implicitly embed knowledge about the embodiment.

This task can be described as a non-linear supervised learning problem in terms of machine learning. As an example, motor commands (for instance, in the form of joint positions) generate a body pose (as sensed by a vision system) according to a complex non-linear latent function (the *forward kinematics*). Supervised learning creates an internal model (that can be called a *sensorimotor map* in analogy to the human brain) of how the generating motor control signals and resulting sensor signals are connected from a set of samples observed during a training phase. The biggest challenge in sensorimotor learning lies in the high-dimensionality of the motor control signals. The higher the number of degrees of freedom a robot can control, the more complex the latent function becomes. As a consequence, sensorimotor learning on a full humanoid robot can be a time-consuming or even intractable task requiring a number of training samples that is exponential in the number of degrees of freedom.

In the domain of machine learning, there are methods known that have successfully been applied for sensorimotor learning such as artificial neural networks, and statistical and stochastic learning. To evade the problem of exponential growth, most methods resort to learning local approximations rather than creating a complete sensorimotor map (e.g., the *Locally Weighted Projection Regression*[1]). While this enables fast and nearly instantaneous learning, these models can only predict configurations of the body similar to those encountered during training (i.e., generalization) but extrapolate poorly to completely unknown variations. An extensive overview over the available methods and their application in sensorimotor and body schema learning is provided in [2], [3].

In our work, we developed the *Kinematics* and *Dynamic Bézier Maps*[4], [5]. These representations follow a different approach in the sense of not being *general* representations for supervised learning but are specialized to the *forward kinematic* and *inverse dynamic* latent functions. Relying on mathematical representations from the domain of computer graphics (namely, rational polynomial approximation and tensor-product Bézier forms), the classes of latent functions can be expressed in a *linear form* with a fixed number of parameters exponential in the number $n$ of degrees of freedom of the robot. For instance, the KBM form of the forward kinematics can be expressed by the formula:

$$f(\boldsymbol{\theta}) = \sum_{i=1}^{3^n} \boldsymbol{b}_i \cdot B_i(\boldsymbol{\theta})$$

This involves a a-priori known and non-linear basis transformation $B_i(\cdot)$ of the motor control signals.

The KBM and DBM models expose very intriguing characteristics. First, they can be constructed directly from traditional models and provide an *exact* encoding of the latent functions. This also happens when learning in the absence of sensor noise (e.g., in simulation). Second, very efficient algorithms can be used to learn the model due to the linear form including *fast incremental online learning*, and *batch learning* with *partial least squares* or *Bayesian regression*. As a result, learning can be *substantially faster* while maintaining a *high resistance to sensor noise*. Third, the models are *global*, that is, learning even in a restricted range of the configuration space during training generates a global model of the latent function. This allows, for instance, the prediction of body configurations not observed during training (i.e., *extrapolation*). Finally, the KBM and DBM form expose only very few hyper parameters that have only a weak impact on the learning quality and can therefore be integrated very easily into existing systems.

Learning with these novel representations has been implemented on the humanoid robot ARMAR-III for using simple tools that extend the robot's reach and as a live-long learning process to improve manipulation tasks (e.g., grasping without need for visual servoing).

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