**Research Statement (describe your research, interests and future work at IAS in 500 words; do not write a letter)**

* Machine Learning for Robotics (especially Reinforcement Learning, Imitation, and Model Learning)
* Robot Grasping and Manipulation
* Robot Control, Learning for Control
* Robot Table Tennis
* The IAS Lab aims at endowing robots with the ability to learn new tasks and adapt their behavior to their environment. To accomplish this goal, IAS focuses on the intersection between Machine Learning, Robotics and Biomimetic Systems.-->**Biomimetics** or **biomimicry** is the imitation of the models, systems, and elements of nature for the purpose of solving complex [human](http://en.wikipedia.org/wiki/Human) problems.
* Resulting research topics range from algorithm development in machine learning over robot grasping/manipulation and robot table tennis to biomimetic motor control/learning and brain-robot interfaces.
* The goal of bringing advanced motor skills to robotics using techniques from machine learning and control.

# Research Overview

* Creating robots that can learn to accomplish many different tasks triggered by environmental context or higher-level instruction.

### Motor Skill Learning : three layers of abstraction

* Learning to Execute:
  + An essential problem in robotics is the accurate execution of desired movements using only low-gain controls such that the robot will accomplish the desired task while not harming human beings in its environment.
  + Following a trajectory with little feedback requires the accurate prediction of the needed torques, which cannot be achieved using classical methods for sufficiently complex robots.
  + However, learning such models is hard as the joint-space can never be fully explored and the learning algorithm has to cope with a never-ending data stream in real time.
  + We have developed learning methods both for accomplishing tasks represented in [operational space](http://www.ausy.tu-darmstadt.de/Research/LearningOperationalSpaceControl) as well as in [joint-space](http://www.ausy.tu-darmstadt.de/Research/LearningModelsForControl).
  + OPERATIONAL SPACE - Learning Operational Space Control (OSC)
    - Its potential for dynamically consistent control, compliant control, force control, and hierarchical control has not been exhausted to date.
    - Applications of OSC range from end-effector control of manipulators up to balancing and gait execution for humanoid robots
    - the practical use of operational space control becomes in-creasingly difficult in the presence of unmodeled nonlinearities, leading to reduced accuracy or even unpredictable and unstable null-space behavior in the robot system.
    - Learning methods do not easily provide the highly structured knowledge required in traditional operational space control laws, e.g., Jacobians, inertia matrices, and Coriolis/centripetal and gravity forces, since all these terms are not always instantly observable. They are therefore not suitable for formulating supervised learning as traditionally used in learning control approaches.
    - we have designed novel approaches to learning operational space control that avoid extracting such structured knowledge and rather aim at learning the operational space control law directly, i.e., we pose OSC as a direct inverse model learning problem.
    - A first important insight for this project is that a physically correct solution to the inverse problem with redundant degrees-of-freedom does exist when learning of the inverse map is performed in a suitable piecewise linear way.
    - The second crucial component for our work is based on the insight that many operational space controllers can be understood in terms of a constrained optimal control problem.
    - The cost function associated with this optimal control problem allows us to formulate a learning algorithm that automatically synthesizes a globally consistent desired resolution of redundancy while learning the operational space controller. From the machine learning point of view, this learning problem corresponds to a reinforcement learning problem that maximizes an immediate reward. We employ an expectation-maximization policy search algorithm in order to solve this problem.
  + JOINT-SPACE - Learning Models for Control
    - Bringing anthropomorphic robots into human daily life requires backdrivable robots with compliant control in order to ensure the safe interaction with human beings. controllers allow the robot to automatically adapt its shape to changes in its environment. To achieve accurate but compliant tracking, it is essential to predict the torques required for the current movement accurately.
    - It is well-known that for sufficiently complex robots (e.g., humanoids, service robots), the standard rigid body dynamics (RBD) models no longer describe the dynamics properly, and data-driven approximate methods become a promising alternative.
    - Machine learning techniques has a multitude of advantages ranging from higher precision torque prediction to adaptation to altered dynamics with online learning.
    - Online learning of robot dynamics poses a tremendous technical challenge as the learning method has to deal with an endless stream of data while learning needs to take place in real-time.
    - While modern machine learning approaches such as Gaussian process regression and support vector regression, yield significantly higher accuracy than traditional RBD models, their computational requirements can become prohibitively costly as they grow with number of data points.
    - One possibility for reducing the computational cost is the partitioning of the data such that only the regionally interesting data is included in a local regression and, subsequently, combining these local predictions into a joint prediction.
    - Another possibility is to employ sparsification methods in combination with an incremental model learning approach [5]. The main idea is to find a sparse representation of the data - called dictionary - which can be used for model learning.
* Learning new Elementary Tasks:
  + LEARNING MOTOR PRIMITIVES
    - Achieving the abilities of learning and improving new motor skills has become an essential component in order to get a step closer to human-like motor skills.
    - Acquire their basic task by imitating human demonstrations and subsequently self-improve by trial and error.
    - Dynamical system-based motor primitives have enabled robots to learn complex tasks ranging from Tennis-swings to legged locomotion. However, most interesting motor learning problems are high-dimensional reinforcement learning problems often beyond the reach of current methods.
    - We use the combination of initializing the learning process by imitation learning and, subsequently, improving the policy by reinforcement learning (with policy gradients)
    - The data is used for imitation learning. We developed a novel EM-inspired reinforcement learning algorithm particularly well-suited for dynamic motor primitives, compared it to several well-known parametrized policy search methods and showed that it outperforms them.
    - Humans learn how to couple their movement primitives with external variables. We proposed an augmented version of the dynamic systems motor primitives which incorporates perceptual coupling to an external variable. The resulting perceptually driven motor primitives include the previous primitives as a special case and can inherit some of their interesting properties.
  + Learning of elementary tasks or movement primitives, which are parameterized task representations based on nonlinear differential equations with desired attractor properties.
  + We mimic how children learn new motor tasks using imitation learning for initializing these movement primitives while employing reinforcement learning to subsequently improve the task performance.
  + In hitting and batting tasks, movement templates with a learned global shape need to be adapted during the execution so that the racket reaches a target position and velocity that will return the ball over to the other side of the net or court.
  + This requires a reformulation of motor primitives to [hitting primitives](http://www.ausy.tu-darmstadt.de/Research/HittingMPs).
  + HITTING PRIMITIVES
    - movement templates with a learned global shape need to be adapted during the execution so that the racket reaches a target position and velocity that will return the ball over to the other side of the net or court.
    - we reformulate the Ijspeert framework to incorporate the possibility of specifying a desired hitting point and a desired hitting velocity
  + A key motor skill for manipulating the environment is [grasping](http://www.ausy.tu-darmstadt.de/Research/LearningToGrasp), which is why one of our research goals is adapting machine learning algorithms to make them applicable in the robot grasping task domain. For grasping or hitting, several alternative motor primitives might be available.
  + GRASPING
    - Our research focuses on the latter and particularily on adapting machine learning algorithms to make them applicable in the robot grasping task domain.
    - The general approach to learning to grasp an object is to initialize the robot's knowledge using imitation learning, and then refining the knowledge by applying reinforcement learning
    - Our first contribution to the field of robot grasping has been the development of an active learning system to allow the robot to find good grasps. The grasping task was approached as a continuum-armed bandit framework, inwhich the hand's pose in the object's reference frame represents the chosen action, and the successfulness of the grasp creates the corresponding reward.
    - The value function was approximated using Gaussian process regression, and local value maxima were determined using a novel method based on Mean-Shift mode detection. Gibb's policy as well as an Upper-Confidence-Bound policy, which incorporates the standard deviation of the GPR, have been implemented to select the grasp that will be attempted. The UCB system has been experimently shown to be very effective at finding suitable grasp location.
* Learning to Compose Complex Tasks:
  + Most complex tasks require several motor primitives to be executed in parallel or in sequence.
  + The selection and composition of motor primitives requires a perceptuo-motor perspective, and is the necessary for [learning complex tasks](http://www.ausy.tu-darmstadt.de/Research/LearningComplexTasks).
  + LEARNING COMPLEX TASKS
    - To date, most of the tasks accomplished by robots is the following of trajectories created manually and often controlled using linear controllers with high gains.
    - Humanoid robots, on the other hand, will require a very different state of the art: motor skills have to be aquired automatically from a mixture of supervised and reinforcement learning, need to have re-usable basic building blocks such as motor primitives and will require complianty control in the respective task spaces.
    - The different tasks need to be able to be ordered in a hierachical fashion.
    - MOTOR PRIMITIVES
      * One of the major challenges in both action generation for robotics and in the understanding of human motor control is to learn the "building blocks of movement generation", called motor primitives. Motor primitives, as used in our group, are parameterized control policies such as splines or nonlinear differential equations with desired attractor properties. While a lot of progress has been made in teaching parameterized motor primitives using supervised or imitation learning, the self-improvement by interaction of the system with the environment remains a challenging problem. In this paper, we evaluate different reinforcement learning approaches for improving the performance of parameterized motor primitives. For pursuing this goal, we researching appropriate imitation and reinforcement learning methods. Our current setup consists out of imitation learning with locally weighted regression and subsequent reinforcement learning with policy gradient methods. We can show that our most modern algorithm, the Episodic Natural Actor-Critic outperforms previous algorithms by at least an order of magnitude. We demonstrate the efficiency of this reinforcement learning method in the application of learning to hit a baseball with an anthropomorphic robot arm. These motor primitives serve as the building blocks of larger scale skill libraries.
    - SKILL LIBRARIES
      * We have discussed how single behaviours in a certain task-space can be learned using parameterized motor primitives and a discussion how to learn the execution of a motor task in its appropriate operational space can be found [here](http://www.ausy.tu-darmstadt.de/Research/RobotControl). It is quite clear, that humans operate in multiple task spaces depending on the accomplished motor skill, e.g., in body-centric or retinal coordinates. However, it appears that the motor primitives used by humans for hand-writing or hand-zig-zagging are exactly the same the ones the same individual would use if using a toe (see e.g., Wing 2000). Thus, the motor primitive programs seem to be invariant under the motor command generation, and using the presented framework, such an invariance should also be easy to achieve by establishing skill libraries. Such skill libraries would contain both motor primitives as well as motor command transformations in order to make many combinations of the two possible. In such a case, a particular skill consists out of combination of the transformation of a motor command into the respective task-space and a primitive motor program which prescribes the behaviour. A motor skill is triggered from a perceptual system which selects the appropriate skill for the task. However, the learning of such skills will be largely using the methods presented in this thesis. It will use the observed movements in order to learn coordinate system to motor command transformations, even if the performed task was in a different coordinate system. Separately from the task primitive to motor command transformation, we will learn motor primitives. For this, observed tasks are compared to existing primitives. If the observed task is equivalent to an existing one, it will be used for refining the primitive while otherwise it will it will be added to the skill library. Subsequently, the skill library manager needs to decide whether to practice the skill using the reinforcement learning methods found [here](http://www.ausy.tu-darmstadt.de/Research/ReinforcementLearning).
    - LEARNING TO SELECT SKILLS
      * The selection of skills shifts the focus away from the pure motor control towards a perceptuo-motor perspective. In this case, a general task is given, e.g., grasp a specified object and pick it up, move through the room along a global trajectory, or hit a ball with a tennis racket. Here, perceptual variables allow us to choose the right motor primitives, e.g., whether to select a power grasp vs a precision pinch for a particular object, which foot trajectories to use for moving from one foothold to another in the presence of obstacles, or whether to select a tennis fore- vs backhand. Similarly, they need to be used in order to set the motor primitive goal parameters, e.g., the contact points where we intend to hold the object, the selected next foothold, or where to hit the ball at what time. Each of these tasks is associated with the appropriate effector. However, it is quite obvious that some of the tasks do transfer between end-effectors, e.g., we could use two fingers or two hands for generating a precision pinch for grasping and lifting a particular object. Clearly, the next higher system above the skill selection system needs some form of higher-level intelligence which determines the general task. This layer could close the gap between artificial intelligence systems and robotics.
    - MOTOR PRIMITIVE SEQUENCING AND PARALLELIZATION
      * Another key issue for research is the parallelization and sequencing of motor primitives. Such issues automatically arise in tasks of higher complexity, e.g., assembling a modular system such as an IKEA shelf. For such tasks, we require a sequence of tasks such as first several a peg-in-the-hole tasks (e.g., see Gullapalli et al., 1994) and subsequently dropping a shelf on top of the four pegs. It will also require holding two sides of the shelf in parallel so that they do not fall before assembled together. In order to learn such tasks, we require a hybrid control architecture consisting out of the lower level components such as motor primitives and task execution as well as a higher, discrete layer. The state of this discrete layer are the active primitives which together form a macro state or option. Such approaches will require a fusion of previous approaches to hybrid control approaches, hierarchical reinforcement learning and imitation learning similar as discussed my thesis proposal. Working towards such complex task compositions is of essential importance for the future of motor skills in robotics.
  + An example of a complex tasks which requires motor primitive selection and hitting primitives is the task of [learning to play ping-pong](http://www.ausy.tu-darmstadt.de/Research/LearningToPlayPing-pong). Moving towards learning complex tasks requires the solution of a variety of hard problems.
  + LEARNING TO PLAY PING-PONG
    - Human motor control appears to rely on motor primitives that encode basic movements as the elementary units of motor actions. Many resulting models in computational motor control assume that a hierarchical composition of elementary templates allows humans to perform difficult task. As this concept makes sense in the context of robotics, there has been an increasing number of motor learning approaches in robotics research that rely it. Formalizations in terms of dynamic systems have lead to biomimetic robot systems that allowed learning a large variety of basic movements that include both rhythmic movements (e.g., drumming, paddling a ball on a string, basic gaits of biped and quadroped robots, etc) as well as single-stroke discrete movements (e.g., hitting a baseball, ball in a cup movements, etc).
    - Nevertheless, while the general ideas of motor primitives has inspired successful applications of biomimetic robotics, these have not yet caught up with computational motor control models to date. Instead of learning complex tasks using these basic elements, they are currently only employed in order to acquire and refine simple tasks that do not require a central, supervisory process for decision making. For complex tasks in robotics such as sports or manipulation in cluttered environments, such a supervisory process will become essential.
    - In this project, we will study how robots can learn complex tasks using motor primitives inspired results from human motor control that will be employed by a central, supervisory process for higher level decision making. As an example, we will learn to play table tennis in the way how humans acquire the motor skill for such hitting sports. Table tennis provides us with a unique scenario that has all the complexity common in motor skills learned by humans. In a feasibility study, we have created a mechanical model based biological hypotheses (e.g., Durrey's movement phases, Ramanantsoa virtual hitting point hypotheses, operational timing hypothesis, etc) and, as a result, are able to ensure that our learning approach will be applicable in this context.
    - Our suggested approach can be decomposed into two parts: Firstly, the robot will acquire a few motor primitives through imitation and, subsequently, will refine these using a ball gun by reinforcement learning. Our previous work on discrete motor primitives provides us with these basic components and can be applied in this first step. Secondly, we focus on learning the central process for using motor primtives that biological systems appear to have but biomimetic robots lack. This supervisor will make usage of context information (e.g., predicted ball trajectories, opponents behavior) in order to select motor primitives, generalize between primitives, determine goal parameters (e.g., virtual hitting points, timing).
  + Among these are the decomposition of large tasks into movement primitives (MP), the acquisition and self-improvement of MPs, the determination of the number of MPs in a data set, the determination of the relevant task-space, perceptual context estimation and goal learning for MPs, as well as the composition of MPs for new complex tasks.
  + These questions are tackled in order to make progress towards fast and general motor skill learning for robotics.

## Imitation Learning

* Research in robotics and artificial intelligence has lead to the development of complex robots such as humanoids and androids.
* In order to be meaningfully applied in human-inhabited environments, robots need to possess a variety of physical abilities and skills. However, programming such skills is a labour- and time intensive task which requires a large amount of expert knowledge. In particular, it often involves transforming intuitive concepts of motions and actions into formal mathematical descriptions and algorithms.
* To overcome such difficulties, we use imitation learning to teach robots new motor skills. A human demonstrator first provides one or several examples of the the skill. Information recorded through motion capture or physical interaction is used by the robot to automatically generate a controller that can replicate the seen movements. This is done using modern machine learning techniques. Imitation learning also allows robots to improve upon the observed behavior. This so called self-improvement of the task can help the robot to adapt the learned movement to the characteristics of its own body or the requirements of the current context. Hence, even if the examples presented by the human are not optimal, the robot can still use them to bootstrap its behavior.
* At IAS, imitation learning has already been used to teach complex motor skills to various kinds of robots. This includes skills such as locomotion, [grasping of novel objects](http://www.ausy.tu-darmstadt.de/Research/LearningToGrasp) , [ping-pong](http://www.ausy.tu-darmstadt.de/Research/LearningToPlayPing-pong), [ball-in-the-cup](http://www.ausy.tu-darmstadt.de/Research/LearningMotorPrimitives) and tetherball. New machine learning methods that reduce the time needed to acquire a motor skill are developed. The goal of this research is to have intelligent robots that can autonomously enlarge their [repertoire of skills](http://www.ausy.tu-darmstadt.de/Research/LearningComplexTasks) by observing or interacting with human teachers.

## Reinforcement Learning

Efficient reinforcement learning for continuous states and actions is essential for robotics and control. We follow two approaches depending on the dimensionality of the domain. For high-dimensional

state and action spaces, it is often easier to directly learn policies without estimating accurate system models. The resulting algorithms are parametric policy search algorithms inspired by expectation-maximization methods and can be employed for [motor primitive learning](http://www.ausy.tu-darmstadt.de/Research/LearningMotorPrimitives). For lower-dimensional systems, Bayesian approaches to control can be shown to be able to cope with the optimization bias introduced by the model errors in model-based reinforcement learning. As a result, these methods can learn good policies at a rapid pace based on only little interaction of the system. Supervised learning is not always sufficient for motor learning problems, partly because often an expert teacher or idealized version of the behavior is not available. Because of that, one of our goals it the development reinforcement learning methods which scale into the dimensionality of humanoid robots and can generate actions for seven or more degrees of freedom.

Our general goal in reinforcement learning is the development of methods which scale into the dimensionality of humanoid robots which is a tremendous challenge for reinforcement learning as a complete exploration of the underlying state-action spaces is impossible and few existing techniques scale into this domain. Therefore we rely upon a combination of both, watching a teacher and subsequent self-improvement. In more technical terms: first, a control policy is obtained by imitation and then improved using reinforcement learning.

Parametrized policies allow an efficient abstraction of the high-dimensional continuous action spaces which is often needed in robotics. We can directly optimize the parameters of the primitive by the use of policy search methods

Members of IAS have developed a variety of novel algorithms for this context which have been applied for learning to play table tennis, the game 'Ball in the Cup' or darts.

A.) Natural Actor-Critic (NAC): The NAC is currently considered the most efficient policy gradient method. It makes use of the fact, that a natural gradient usually beats a vanilla gradient. For more information read:

B.) EM-like Reinforcement Learning: We formulated policy search as an inference problem. This has led to efficient algorithms like reward-weighted regression and PoWER. For more information read:

C.) Relative Entropy Policy Search (REPS): The optimization in policy search can rapidly change the control policy which might lead to suboptimal solutions. REPS solves this problem by bounding the Relative Entropy between two subsequent policies. This allows the derivation of a whole range of new algorithms, including learning hierarchical policies.

## Tactile and Visual Object Exploration

A robot needs to be aware of the properties of objects to efficiently perform tasks with them. Currently, most robots are provided with this object information by a programmer. However, autonomous robots working in service industries and domestic settings will need to perform tasks with novel objects. Hence, relying on predefined object knowledge will not be an option.

Instead, robots will have to learn about objects by exploring their properties through physical interactions, such as pushing, stroking, and lifting. As random exploration is an inefficient approach, we develop methods for efficiently gathering information.

The fundamental knowledge learned about objects and primitive actions will later on form the basis for learning complex behaviors and predicting the properties of novel objects. By discovering accurate representations of objects, the robot will be able to plan and execute manipulations more precisely.

A) Learning Tactile Sensing using Vision: The textures of object surfaces can be observed both by visual inspection and by sliding a dynamic tactile sensor across the surface. The robot can combine these types of sensor readings to determine which components of the data contain information pertaining to the texture.

In particular, the robot can find the components that are maximally correlated between the two sensor modalities. Given the relevant data components, the robot can create a compact representation of object textures, which allows it to distinguish between surfaces more accurately.

B) Active Learning of Object Properties: Learning about objects is not a passive perceptual process: its embodiment allows a robot to discover object properties by actively changing its point of view and by interacting with objects. At the same time, the robot observes the effect of its actions and learns how it can bring about desired effects.

To learn efficiently, the robot should select the exploratory actions that yields the highest information gain out of all possible actions. By efficiently exploring its environment, a robot develops object knowledge grounded in its sensorimotor experience.

The developed object knowledge can be used to manipulate previously unknown objects in unstructured environments. For example, the robot could teach itself to perform tasks in domestic environments.

## Robot Grasping and Manipulation

A key long-term goal of robotics is to create autonomous robots that can perform a wide range of tasks to help humans in daily life. One of the main requirements of such domestic and service robots is the ability to manipulate a wide range of objects in their surroundings.

Modern industrial robots usually only have to manipulate a single set of identical objects, using preprogrammed actions. However, future service robots will need to operate in unstructured environments and perform tasks with novel objects. These robots will therefore need to learn to optimize their actions to specific objects, as well as generalize their actions between objects.

A) Improving Grasps through Experience: The ability to grasp objects is an important prerequisite for performing various manipulation tasks. Using trial-and-error, a robot can autonomously optimize its grasps of objects. In particular, the grasp selection process can be framed as a continuum-armed bandit reinforcement learning problem. Thus, the robot can actively balance executing grasps that are known to be good and exploring new grasps that may be better.

B) Affordance Learning: An object's affordances are the actions that the robot can perform using the object. The affordances of basic objects, such as tools, are usually defined by their surface structures. By finding similar surface structures in different objects, the robot can transfer its knowledge of afforded actions between objects. In this manner, the robot can predict whether a novel object affords a specific action, as well as adapt the action to this object.

The robot can learn an initial action from a human demonstration. Adapting this action to new objects is achieved autonomously by the robot, using a trial-and-error learning approach.

## Biomimetic Robotics, Human Motor Control and Brain-Robot Interfaces

An different research goal focuses on human motion: using the tools that we develop for robot motor learning may be beneficial to understand human motor control as well as be used in [brain-robot interfaces](http://www.ausy.tu-darmstadt.de/Research/BCIRoboticsRehabilitation) that learn to help stroke patients to rehabilitate. For more information on some of our work in this context see:

**OTHERS**

* IAS members maintain a presence at the Max Planck Institute for Intelligent Systems in Tuebingen and there will always be opportunities there as well.
* Computational Learning for Autonomous Systems (CLAS) and Intelligent Autonomous Systems (IAS)