Robot Navigation Based On Ego Perspective Images

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Abstract We present an adaptive control system for navigating a robot using camera images only. The novelty of the system is its visual processing which generates a Fourier expansion on the environment in which the robot acts.

Applying reinforcement learning methods on real world problems always induces the problem of extracting states out of raw sensor data. In our case the robot has to detect its position (the state) by means of images from a head-mounted camera. With the extracted state at hand, the robots control is learned by the *least squares policy iteration* (LSPI) framework [1]. As many popular algorithms, LSPI employs a linear Q-value estimator in a feature space setting, e.g. allows for a continuous state space. In such a setting, a successful policy depends on the ability to approximate the Q-value function. From approximation theory it is known that the choice of feature space largely influences the quality of function approximation. For linear estimators, naturally suited feature spaces include polynomials, trigonometric polynomials and splines. However, video images are certainly *not* suitable.

We propose the use of an unsupervised method, called *slow feature analysis* (SFA [2]), to learn a mapping from images into a suitable feature space. Given a slow random walk across the state space, SFA aims to minimize the temporal change of the learned feature output. A set of constraints avoid trivial solutions as well as giving the *slowest functions possible* (that fulfill the constraints) the shape of trigonometric basis functions on the state space [3]. In theory, given an infinite training sequence and unrestricted model class, SFA maps observations into the space of trigonometric polynomials *irrespectively* of the sensor at hand. In reality, however, restrictions by model class and problem complexity lead only to approximations thereof.

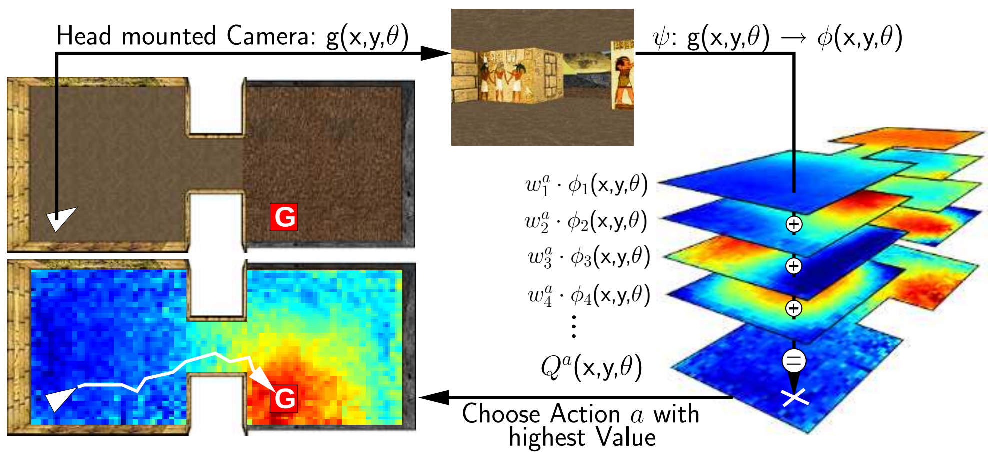

Figure 1: *Navigation control:* The robots view (interpreted as current state) is mapped into a feature space suitable for linear Q-value approximation. The action with highest Q-value is selected until the rewarded goal area **G** is reached.

To improve this approximation, we constructed a kernelized SFA algorithm analogous to *kernel PCA* [4], which outperformed its linear counterpart considerably. In order to deal with the huge amount of training samples needed to catch the statistics of real images, we employed a sparse kernel matrix approximation method first introduced by Csató and Opper [5]. One can control the model complexity, and therefore the approximation quality, through the size of the support vector set.

Estimating camera positions out of video images is well studied in the field of *simultaneous localization and mapping* (SLAM, e.g. [6]). This approach relies heavily on prior knowledge of environment and sensor configuration. While this is fine from an engineers point of view, we wanted to learn the preprocessing with as little prior knowledge as possible. In this attempt we resemble some biological inspired work [7]. However, our method is currently founded on allothetic (feed forward) information and has yet to include idiothetic information (i.e. short-term memory) to be comparable to those works.

We evaluated our method at simulations and on a real robot in a small rectangular environment. Our analysis showed that the approach is sound in principle, but also identified obstacles that demonstrate shortcomings in the general policy iteration framework.

References

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