Dynamic Movement Primitives

- are a method for trajectory planning
- define a way to adjust complex inputs *without* **manual parameter tuning** and **instability issues**.
- each DMP is a nonlinear dynamical system

Key ingredients

- Take a stable, well defined dynamical system and add a term that makes it follow a specific trajectory.

Discrete DMPs

The stable dynamical system in this case is the **point attractor** system:

$$\ddot{y} = \alpha_y(\beta_y(y_{des} - y) - \dot{y}).$$

We add to this the nonlinear **forcing function** f to obtain:

$$\ddot{y} = \alpha_y(\beta_y(y_{des} - y) - \dot{y}) + f,$$

where $f = \frac{\sum_{i=1}^{N} w_i \psi_i}{\sum_{i=1}^{N} \psi_i} x(y_{des} - y_0),$ for $\psi_i = \exp(-h_i(x - c_i)^2)$, which acts as a Gaussian – h_i defines the variance, c_i the mean.

- x is the *canonical dynamical system* $\dot{x} = -\alpha_x x$, which acts as a diminishing term driving f to zero, and leaving only the point attractor dynamics.

- Spatial and temporal scaling allows stretching or compressing of the trajectory in spatial (y) and temporal (t) domain.

Comments

- How to choose means (centers) and the variances of basis functions ψ_i?

There two common ways of choosing the centers of basis functions; by spreading them uniformly on the time axis, or by distributing them according to the complexity of the desired trajectory - more functions around more difficult areas.

The variance parameter can be chosen according to $h_i = \frac{\#basis\_functions}{c_i}$.

- Examples of DMPs in action?

Imitating desired paths. We can choose f such that our trajectory imitates y_d. By double differentiation of y_d, and some additional manipulation, we can get a supervised version of the problem of estimating the parameters. For that, a simple solution exists.

Other examples, could be found in reinforcement learning, e.g. *Path Integral Policy Improvement*, since we can use DMP to efficiently parametrize and learn policies.