Dynamic Modeling of Robotic Trajectories Using the Parametrized SOM

Antonio C. Padoan Jr. Aluizio F. R. Araújo
Guilherme de A. Barreto
Departamento de Engenharia Elétrica, Universidade de São Paulo (USP)
Av. Trabalhador Sancarlense, 400, 13566-590, São Carlos, São Paulo, Brasil
{padoan,aluizioa,gbarreto}@sel.eesc.sc.usp.br

1 Problem Descrition and Objectives

Planning and control of robotic trajectories is an important and open issue. In industry, these trajectories are often programmed by an operator who guides the robot trough sequential states and then these positions are stored in memory for later recall. Such a method is neither economical nor fast because of the necessity of a human operator. In addition, if more than one trajectory must be stored, then ambiguities due to repeated states of a trajectory or states shared among the stored trajectories, increase the difficulty of the problem. Then a neural network must learn and associate consecutive states of a trajectory and then reproduce them when necessary. This paper uses an unsupervised neural network model to construct the dynamical modelling of trajectories.

2 The Model

A neural network with a *short term memory* mechanism, was designed to provide the associated joint angles when it receives as input the present and some past states of the robot spatial position. Mathematically, the network must yield the future joint angles vector $\boldsymbol{\theta}(t+1) = f[\boldsymbol{\theta}(t), \ldots, \boldsymbol{\theta}(t-n_\theta+1); \mathbf{p}(t), \ldots, \mathbf{p}(t-n_p+1)]$, where $\mathbf{p} \in \Re^m$ is the spatial end-effector position and $\boldsymbol{\theta} \in \Re^n$ is the vector of the joint angles. The parameters n_p and n_θ are memory delays for joint angles and positions, the function $f(.)$ is the unknown non-linear mapping that the network must learn. In order to make the dynamical modelling of trajectories we choose the SONARX [2]. This model uses the *Self-Organizing Map* (SOM) to approximate the $f(.)$ mapping using just some states of a the trajectory. The SONARX produces discrete points to form the trajectories, then a mechanism to interpolate the information retained in each neuron is used to pose the robot in any spatial position and then achieve accurate responses. This mechanism is the *Parametrized Self-Organizing Map* or PSOM [3]. Using Lagrange coefficients, the PSOM is able to construct a continuous manifold to approximate $f(.)$ propely. The union of the SONARX with the PSOM generated the TEPSOM, i.e., the *Temporal Parametrized Self-Organizing Map*.

3 Results and Conclusion

Simulations for a PUMA 560 robot using trajectories of different degrees of complexity showed that the TEPSOM was more precise then the SONARX and the CHT model [1], both do not parameterize the response space. In the tests were observed the accuracy of the obtained spatial positions and joint angles and the ability to handle repeated positions in the same trajectory such as *eight-shape* trajectory. The TESPOM will be applied to a real PUMA 560 to test the efficiency of the model in planning and control trajectories for this arm.

References

[1] A. F. R. Araújo and G. A. Barreto. Context in temporal sequence processing: A self-organizing approach and its application to robotics. *IEEE Transactions on Neural Networks*, 13(1):45–57, 2002.

[2] G. A. Barreto and A. F. R. Araújo. Self-organizing narx network and its application to prediction of chaotic time series. In *Proc. IEEE-INNS Int. J. Conf. on Neural Nets. (IJCNN'01)*, volume 3, pages 2144–2149, 2001.

[3] J. Walter and H. Ritter. Rapid learning with parametrized self-organizing maps. *Neurocomputing*, 12:131–156, 1996.

Proceedings of the VII Brazilian Symposium on Neural Networks (SBRN'02)
0-7695-1709-9/02 $17.00 © 2002 IEEE