Posters

Miguel Atencia (University of Malaga) and Gonzalo Joya

Parameter estimation for dynamical systems based upon Hopfield and Tank neural networks

Continuous Hopfield neural networks [4] are dynamical systems, inspired by biological neurons, that have been applied to the solution of a number of computational problems, notably associative memory and combinatorial optimization [5]. A method for parameter estimation for dynamical systems has been proposed [3], by using a continuous Hopfield network to minimize the prediction error. Since the proposed method has a natural dynamical definition as an Ordinary Differential Equation, its analysis can be undertaken with the tools of Lyapunov stability theory. It has been proved [2] that, under usual assumptions of persistent excitation, the "Hopfield estimator" converges to the actual values of the parameters, even when they are time-varying. The achievement of estimates with bounded estimation error has also been proved [1] in the presence of disturbances in the system state variables. The methodology can be considered within the framework of robust control (e.g. [6]) rather than in a statistical approach [7], where assumptions on the statistical distribution of the disturbances must be made. Ongoing research aims at determining the robustness margin of the proposed estimator, improve its performance and relax the requirements for persistent excitation.

References

[1] H. Alonso, T. Mendonća, and P. Rocha. Hopfield neural networks for on-line parameter estimation. *Neural Networks*, 22(4):450–462, 2009.
[2] M. Atencia, G. Joya, and F. Sandoval. Parametric identification of robotic systems with stable time-varying Hopfield networks. *Neural Computing & Applications*, 13(4):270–280, 2004.
[3] M. Atencia, G. Joya, and F. Sandoval. Hopfield neural networks for parametric identification of dynamical systems. *Neural Processing Letters*, 21(2):143–152, 2005.
[4] J. J. Hopfield. Neurons with graded response have collective computational properties like those of two-state neurons. *Proceedings of the National Academy of Sciences of the United States of America*, 81(10):3088–3092, 1984.
[5] J. J. Hopfield and D. W. Tank. "Neural" computation of decisions in optimization problems. *Biological Cybernetics*, 52:141–152, 1985.
[6] P. A. Ioannou and J. Sun. *Robust adaptive control.* PTR Prentice-Hall, Upper Saddle River, NJ, 1996.
[7] L. Ljung. *System identification: theory for the user.* Prentice Hall, 1999.

Oksana Chkrebtii (Simon Fraser University), David Campbell, Ben Calderhead and Mark Girolami

Probabilistic integration for inference over differential equation models

We introduce a new methodology for inference on model parameters for systems of ordinary differential equations. Classical estimation approaches construct the likelihood function using numerical solutions that are fully deterministic and thus ignore approximation uncertainty. We propose a probabilistic alternative to using a deterministic solver. The ODE solution is modeled as a stochastic process obtained by a sequential algorithm that samples iteratively from the derivative space and smooths the sampled points via Gaussian process regression. This Bayesian framework incorporates solution uncertainty in the likelihood and thus in the inference process. The poster describes the proposed methodology and its application to simulated data from the FitzHughNagumo system of ODEs.

Anani Lotsi (University of Groningen) and Ernst Wit

Modelling sparse ordinary differential equations (ODEs) using penalized graphical models

Inferring parameters in ODEs from noisy data is a difficult problem (Ramsay 2008, Brunel and d'Alché-Buc, 2007). We aim at recovering the network of the noisy observed data and at the same time capturing the stochastic nature of the biological process as well as their dynamic behavior. It is especially difficult to infer the structure in high dimensional in the so-called "large p, small n" settings (namely when the number of observations is smaller than the dimension of the observed response). This would involve determining structural zeros in the precision matrix or complicated model comparisons. In this work we connect the ODE to a graphical model using various approximations which can be made arbitrarily small via the EM algorithm.

José de Miranda (University of São Paulo)

Estimation of the kernel of a singular integral operator

We address the estimation of the discrete dynamical system generated by the iterations of the singular integral operator $f \to Tf$ defined by

$$Tf(x) = \frac{1}{\int_0^1 K(x,y)f(y)\mathrm{d}y}.$$

We present a methodology for the estimation of the kernel $K(x, y)$ in this operator. This kernel is assumed to be a positive semi-definite symmetric non-negative kernel such that $\int_0^1 K(x, y)dy \geq \delta > 0$. It is also assumed to be square integrable on $[0, 1]^2$. The estimator $\hat{K}$ of K is based on a measured orbit of a function under this dynamics. We will suppose that this orbit does not cycle. Measured points of this orbit, $^{\boxplus}T^i f$, $i \in \mathbb{N}$, are supposed to be of the form $^{\boxplus}T^i f = T^i f + \epsilon_i$ where ϵ_i is i.i.d. functional noise. We prove the consistency of the estimator $\hat{K}$, under some assumptions on the noise.