4 Conclusion

In Section 3.1 we demonstrated the clear and effective application of this method to extract underlying trends from noise time series. This algorithm extends existing techniques of radial basis modelling to model time series that have underlying changes in the dynamics. The remaining examples addressed this application. In each case the addition of time dependent features allowed the modelling algorithm to better fit the data (lower prediction error on fit and test data, and lower minimum description length). Furthermore, in the examples presented in this paper and our other calculations this method has demonstrated the capability to identify bifurcations from a single time series recording. We tested this with data from the Rössler system and the logistic equations, both with and without additive Gaussian noise. The results we obtained were encouraging. Even for moderate noise levels (as in Section 3.2) we were able to identify the main features of the underlying bifurcation. Finally, by applying this method to experimental data (Section 3.4) and computational simulations from an excitable spatio-temporal system (Section 3.5) we were able to extract some time dependent features not evident in the underlying time series. This was most striking for the recording of infant respiration prior to onset of periodic breathing — for this system we identified a period doubling bifurcation.

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