Chapter 7

Conclusions

Local model networks have become popular in the control community during last few years. The idea behind these networks is to divide the operating range of a nonlinear system in many small operating regions so that a relatively simple model can be determined for each of these regions, which can approximate the system behaviour with a sufficient accuracy. Most networks of this class use locally valid linear models and are known as LLM networks. These networks have been applied to identify and control nonlinear systems. Most of the identification techniques developed so far are limited to nonlinear systems in input-output description. The existing control schemes based on the LLM networks can be categorised under master-slave strategies. Methods for the identification of local linear state-space models along with new LLM-based master-slave and non-master-slave control schemes for nonlinear systems are developed in this dissertation. The proposed identification methods and control schemes are investigated in simulation studies and experiments on real plants.

In Chapter 3, different techniques for parameter estimation of local linear state-space models for continuous as well as discrete-time systems are proposed, and corresponding learning algorithms are developed. These techniques can be divided into two classes: local learning techniques and global learning techniques. Local learning algorithms determine the most active local linear
model at current operating point and update its parameters neglecting the non-linearity caused by model switching and overlapping effects. These algorithms are based on the well-known state-variable-filters method and the parameter estimation is performed by using recursive least squares (RLS) or recursive prediction error (RPE) algorithms. Global learning algorithms presented in this chapter minimise a global cost function in order to estimate the parameters of the whole blended model simultaneously using RPE method. With the help of simulation studies, it is shown that the local learning techniques, which are reported to be preferable for the estimation of local linear input-output models (Murray-Smith and Johansen, 1997), fail to converge in the case of state-space models.

Five new adaptive control schemes on the basis of LLM networks are developed in Chapters 4 and 5. Model reference adaptive control (MRAC), adaptive feedforward cancellation (AFC) and LLM-based predictive control schemes proposed in Chapter 4 are based on input-output models of the system. In MRAC a network of local linear controllers is designed for a nonlinear system such that the closed-loop system behaves like a given reference model. The AFC scheme realises an adaptive feedforward compensation of measurable disturbances for a class of nonlinear systems using LLM networks. LLM-based predictive control scheme optimises a future control sequence in order to minimise an objective function. The primary requirements of a predictive control scheme are a good prediction of the future trajectory of the system and the calculation of gradients of the objective function subject to the proposed control sequence. An LLM network as a nonlinear model of the system fulfills both requirements. In addition to delivering a good prediction of system behaviour, this network also provides a set of parameters of the system linearised at each operating point on the predicted trajectory. These parameters are used to calculate the gradients of the objective function directly rather than approximating them with other numerically intensive differentiation techniques. The state-feedback control schemes described in Chapter 5 include LLM-based LQ control and predictive control.

Model reference adaptive control (MRAC), adaptive feedforward cancellation (AFC) and LLM-based LQ control schemes fall into the category of
master-slave schemes. These schemes have advantages and disadvantages. They use two networks, one as identification model and the other as controller. There is a one-to-one correspondence between the components of both networks. The advantage of these schemes is that the parameters of each local controller component can be determined individually by applying linear design techniques. The major drawbacks of these schemes become obvious when they are put in practice to control strongly nonlinear systems with fast moving operating points. In such cases undesired transients are observed even with soft transitions between local controllers.

Results of various simulation studies and laboratory experiments documented in Chapter 6 show satisfactory performance of the proposed identification algorithms. Parameters estimated by global learning algorithms converge to their real values, and the experimental validation of the models of the real plants is successful. In the case of identification of continuous-time local linear state-space models, the parameter estimates delivered by continuous-discrete identification setup are more accurate than those estimated for delta-operator models. But the former is computationally more expensive than the latter. The master-slave control schemes perform well as long as the operating point is moving slowly or the differences in the dynamics of local models are not large. These schemes face transition problems with fast moving operating point. The predictive control schemes based on LLM networks do not suffer from such transition problems. The reason is that, in predictive control, future control strategy is devised keeping these inter-model transitions in mind. The basic requirement for the success of predictive control is that all the local models, which are used in a prediction horizon, must deliver local estimates of system parameters within some error bounds.

Master-slave control configuration is an outcome of the desire to utilise linear design techniques in nonlinear control. In case of a linear controller design a transfer function or a time-invariant state-space model of the system is used. The major assumption for the design is that the system is fully described by the given model and its parameters are not going to change in the future. This assumption leads to determine an infinite horizon controller, which has fixed parameters. The desired control performance is guaranteed as long as the as-
assumption remains valid. In a master-slave scheme for nonlinear systems this assumption remains no longer valid if the operating point is moving among local models and the control performance is deteriorated. This deterioration is dependent, on one hand, on the discrepancies between the dynamics of the local models, which successively become active, and on the other hand, on the rate of change of the operating point. LLM-based predictive control schemes perform better than master-slave schemes, but are computationally more expensive. Furthermore, the predictive control schemes are more sensitive to model uncertainties and require a good model.

During the design of LLM-based control schemes, the global stability of the closed-loop system has not been considered in this work. The future research may be focused on the global design procedures for the local controllers such that the stability of the closed-loop system can be guaranteed.