POPULAR SCIENCE SUMMARY

Process identification is the field of mathematical modeling of processes (systems or signals) from experimental data. The past three decades have brought a large number of really challenging applications of identification of nonstationary processes, i.e., processes with time-varying characteristics, in different areas such as telecommunications, signal processing and automatic control. The existing approaches to identification of nonstationary processes can be coarsely divided into model-free and model-based solutions. In the model-free case no explicit description of process parameter variation is adopted. Instead, assuming that unknown process parameters vary “sufficiently slowly” so that it can be regarded as locally stationary, identification can be carried out using the localized (weighted or windowed) versions of the least squares or maximum likelihood estimators, or using the gradient algorithms. When the model-based approach is taken, an explicit model of parameter changes is incorporated, either deterministic or stochastic (random). In the deterministic setup, parameter trajectories are approximated by linear combinations of a certain number of known functions of time, called basis functions. Parameter estimates can be obtained by means of estimation of the best-fitting approximation coefficients. In the stochastic case, a stochastic description of parameter variation is adopted, such as the integrated random walk model of a certain order (perturbed polynomial model). Then, after state space embedding, the problem of estimation of process parameters can be solved using the algorithms known as Kalman filters.

The project aims at describing and analyzing a new class of identification algorithms which combine the basis functions approach with the local estimation technique. Unlike the classical basis functions approach, which yields interval estimates of the parameter trajectory, the proposed noncausal weighted basis functions estimators will be used to obtain a sequence of point estimates corresponding to particular instants of time. This means that the estimation procedure will be carried out independently for each instant t, based on the input/output data gathered in the local analysis interval centered at t. Noncausal estimation schemes, such as the proposed one, can significantly reduce the bias component of the mean square parameter estimation error. Owing to this, their estimation performance is usually much better than that of the comparable causal schemes. Since at each instant of time noncausal estimators rely on both “past” and “future” process observations, they cannot be used in real-time applications such as adaptive prediction or adaptive control. However, many other applications exist, such as parametric spectrum estimation, predictive coding of signals or simulation of nonstationary processes, that are not time-critical in the sense that the model-based decisions can be delayed by a certain number of sampling intervals. Such a processing mode is often referred to as almost real time. The new class of estimators can be incorporated in such applications.

The proposed approach will be the first unified treatment of noncausal identification schemes that combine the local estimation framework with the basis functions approach, and are valid for arbitrary weighting sequences and any selection of the functional basis. Based on the results of theoretical analysis, we plan to solve all major problems associated with implementation of such estimators, including rationalization of the choice of functional basis and the shape of the weighting sequence, adaptive selection of the size of the local analysis interval and the number of basis functions, and significant reduction of complexity of the computational algorithms without compromising their estimation performance. The results of the project should be interesting, both from the theoretical and practical viewpoint, to all researchers working in the field of nonstationary system/signal identification and its applications.