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Identification of Time-Varying Non-Linear Systems for Brain Connectivity Analysis

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Editorial

Many control systems encountered in physical, automobile engineering, economic phenomena and biomedical engineering fields are nonlinear and nonstationary to some extent. In general, nonlinear processes can be adequately characterized by a nonlinear model. Recently, a system can be obtained directly from experimental input/output data by determining the system structure and the numerical values of the unknown parameters, this process is known as system identification. System identification techniques for linear and nonlinear systems have received such attention and have been widely applied to reveal fundamental properties of the system which are not apparent. Billings [1] surveyed the available approaches of non-linear system identification by considering the functional series of Volterra and Wiener, and the identification algorithms developed by Ku and Wolf [2]. Narendra and Parthasarathy [3] considered the orthogonal expansion methods and the kernel identification algorithms. All these methods discussed above were considered numerous alternatives and related topics which have been developed over the last decade or so.

Time-varying non-linear system identification has been the subject of intensive research for many years, and fruitful results have been reported. Billings et al. provided an overview of a nonlinear system identification methodology based on the NARMAX (Nonlinear Autoregressive Moving Average with exogenous inputs) model [4,5], which is a general representation of a nonlinear dynamical system by taking the form of a nonlinear difference equation. The NARMAX methodology can provide a unified solution to this equation only using experimental data recorded from the system of interest. The process of identifying a NARMAX model usually includes determining the structure of the unknown nonlinear equation, estimating the coefficients or parameters associated with the particular form or structure and finally validating the identifying model in order to ensure that it can describe the real life system accurately. These time-variant parameters in NARMAX model are further estimated to unveil the fundamental dynamical properties of the model based on Kalman Filter, Least Mean Squares and Recursive Least Squares approaches.

The NARMAX methodology are increasingly used tools for exploring causal interactions by combining modern causality theory with multivariate time-series analysis, and has been derived from methodological and application-related research objectives at the frontier of computational and clinical neurosciences. Some authors have used the classical time-invariant NARMAX approaches to derive directed measures of interaction to fit multivariate autoregressive model. For high-dimensional data, spurious interaction between different components may appear because of the influence of other common source. Therefore, it is significant to differentiate between causal and non-causal or indirect interactions. Different methods have been developed that search for the interaction between different components, while excluding the influence of other components. NARMAX models have been verified an appropriate analysis tools for practical applications. Additionally, compared with other non-linear models, NARMAX models are more easily interpretable and tractable. Therefore, the NARMAX model methods have been widely discussed by Billings [6] and are very suitable as a methodological basis for the interaction analysis of physiological sequences provided by the underlying clinical and experimental studies to compute dynamic interaction profiles. Bootstrap methods can then be used for statistical testing. Additionally, the methodological approaches can be used in other research areas which deal with interaction analysis (e.g. machine diagnosis, seismology, automobile engineering, and analysis of biological interactions).

We hope this editorial will provide a useful reference for researchers working in the system identification, brain connectivity analysis and related application areas, and help academics, neuroscientists, and engineers explore new methodologies in both theory investigation and practical applications.

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