520a Simpca with Modified Instrumental Variable to Improve Estimation Accuracy

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Based on projection techniques in Euclidean space, subspace identification methods (SIMs) have been one of the main streams of research in system identification (Gevers, 2003). Several representative algorithms have been published, including canonical variate analysis (CVA, Larimore, 1983; 1990), numerical algorithm of subspace state space system identification (N4SID, Van Overschee and De Moor, 1994) and multivariate output-error state space (MOESP, Verhaegen, 1994). The asymptotic properties of these subspace algorithms also have been investigated in the past decade and consistency conditions of the estimates have been identified (Deistler et al., 1995; Peternell et al., 1996; Jansson and Wahlberg, 1998; Bauer et al., 1999; Bauer and Jansson, 2000; Knudsen, 2001). The effect of weighting matrices and more explicit expressions for the asymptotic variance of the model estimates have been obtained recently (Bauer and Ljung, 2002; Gustafsson, 2002).

SIMs have many advantages compared to prediction error method, such as its simplicity in parameterization, better numerical reliability and modest computational complexity. However, they also have certain drawbacks. One is that SIMs may give biased estimate for errors-in-variables; another is that many SIMs do not work on closed-loop data (Ljung and McKelvey, 1996; Forssell and Ljung, 1999), even though the data satisfy identifiability conditions for prediction error methods.

SIMPCA, known as subspace identification method via principal component analysis, is the method we recently developed to address these two aspects. While most existing subspace identification methods use the observable subspace to estimate the observability matrix, SIMPCA uses the null space or parity space that has been used in fault detection literature to extract the system information. SIMPCA makes use of PCA to extract the extended observability matrix Gamma_f and Toeplitz matrix H_f from input and output data, much similar to the total least squares in the sense that both input and output variables are included in the PCA decomposition, which naturally handles errors-in-variables situation. SIMPCA with a column weighting is also proposed (Wang and Qin, 2004) to improve the accuracy in the model estimates.

In this work, we modified the instrumental variable and corresponding weighting applied in SIMPCA which can significantly improve the estimate accuracy of system, to be specific, the system zero estimation, especially in the errors-in-variables case. The modified instrumental variable also improves the system order estimation via AIC index. We give geometric interpretations of the difference between SIMPCA with modified instrumental variable and CVA. The performance of original SIMPCA, modified SIMPCA, MOESP and CVA are compared through a simulation example.

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