Detection of Multivariable System noise degradation

A. Pouliezos, G. Stavrakakis, G. Tselentis
Technical University of Crete
73133 Chania, Crete

Extended Abstract

Fault detection has by now become an important section of Control theory and practice. Fault detection methods for various fault categories exist and are currently supplemented by non-model, knowledge-based and neural network methods (see for example Naidu et al., 1990, Tzafestas, 1989).

In this paper a model-based two-stage method is presented which is capable of performing all the necessary tasks of a fault monitoring system in the case of additional plant and observation sensor noise. These are:

- fault detection (alarm)
- fault isolation (what has failed)
- fault identification (size of fault)
- system reorganization (resetting of filter and fault monitor parameters).

Since the optimal operation of the Kalman filter state estimator depends on the correctness of the system parameters, it is necessary that they are constantly monitored to check whether they remain in acceptable statistical limits, given their pre-estimated values. In particular, both the plant and observation sensor noise covariance, which enters into the filter calculations, affect the state estimate error covariance and thus if increased produces suboptimal state estimates, i.e. estimates with larger error covariance. Therefore, it is important to have a plant and an observation sensor noise covariance fault detector, if the optimality of the Kalman filter is desired under every operating condition.

Furthermore the proposed methodology can be applied to two other

circumstances as well:

- In the case were the plant and sensor noise covariance is completely unknown and thus simultaneous state estimation and plant or sensor noise covariance identification is needed. In this case, an initial estimate of the noise covariance is used and subsequently the fault monitoring scheme "detects" the correct value.

- In the case where the plant and/or sensor noise covariance is slowly changing (but slower than the time needed for the fault monitoring scheme to respond). In this case the proposed methodology can be used to "track" the covariance value.

Moreover, FDI (Fault Detection and Identification) plays an important part in the design of autonomous control systems (Zeigler et al., 1991). Indeed a well designed autonomous control system must incorporate some form of low and high level fault detection subsystem.

Previous attempts for the solution of this problem have aimed only at the detection phase of the fault monitoring process: Liu, 1977, has used SPR (Sequential Probability Ratio) and GLR (Generalised Likelihood Ratio) for sensor noise degradation detection. Although GLR can, in theory, perform all required tasks, no practical implementation was presented. Uosaki and Kawagoe, 1988, propose a backward SPRT (Sequential Probability Ratio Test) for the detection of the innovations variance change.

In this paper a mixed strategy for performing the aforementioned tasks is adopted. Using GLR system modelling, the effect of increased plant and/or sensor noise covariance on the joint pdf of the Kalman filter innovations is calculated. Then, operating on sliding windows of innovations data, hypothesis testing on the innovations variance is used to decide whether a plant or sensor degradation (fault) has occurred or not. Using sliding windows of data increases the sensitivity of the detection mechanism. Also, recursive window relations are used for the calculation of the necessary sample statistics, thus making the whole procedure suitable for an on-line computerised supervising-diagnostic system. Following a positive fault decision, the estimated innovations variance is used to calculate the new plant and/or sensor noise covariance. Finally, the relevant Kalman filter and fault monitoring parameters are reinitialised to reflect the latest findings (automatic system reorganisation).

A simulated multivariable system example is also included to illustrate the effectiveness of the method.

REFERENCES

Anderson, T.W. (1984). An introduction to multivariable analysis, 2nd ed. Wiley, New York.

Bartlett, M.S. (1954). A note on multiplying factors for various chi-squared approximations. *J. of the Royal Statistical Society*, Series B, **16**, pp. 296-298.

Kendall, M., Stuart, A. (1979). *The advanced theory of statistics*. Charles Griffin Ltd., London.

Liu, J.S.H. (1977). Detection, isolation, and identification techniques for noisy degradation in linear discrete time systems. Proceedings, 1977 CDC, pp. 1132-1139.

Naidu, S.R., E. Zafiriou, T. J. Mc Avoy (1990). Use of neural networks for sensor failure detection in a control system. *IEEE Control Systems Magazine*, **10**, 7, pp. 49-55.

Ohap, R.F., Stubberud, A.R. (1976). Adaptive minimum variance estimation in discrete time linear systems. In Leondes C.T. (Ed.), *Control and Dynamic Systems*, **12**, pp.583-624, Academic Press.

Pouliezos, A., Stavrakakis, G. (1987). Linear state estimation in the presence of sudden system changes: An expert system. In P. Borne, S. Tzafestas (Eds.), *Applied modelling and simulation of technological systems*, pp. 41-48, North-Holland.

Pouliezos, A., Stavrakakis, G., Tselentis, G. (1991). A two stage real-time fault monitoring system. In S.G Tzafestas (Ed.), *Engineering systems with intelligence*, pp. 653-660, Kluwer Academic.

Priestley, M.B. (1981). Spectral analysis and time series, Vol.1.

Academic Press.

Tzafestas, S.G., Ed., (1989). Knowledge-based system diagnosis, supervision and control. Plenum Press.

Uosaki, K., Kawagoe, M. (1988). Backward SPRT failure detection system for detection of innovation variance change. Proceedings, IFAC Identification and System Parameter Estimation, Beijing, PRC, pp.1153-1157.

Zeigler, B.P., Chi, S.D., Cellier, F.E. (1991). Model-based architecture for high autonomy systems. In S.G Tzafestas (Ed.), *Engineering systems with intelligence*, pp. 3-22, Kluwer Academic.