## Introduction

• Typical fault detection and isolation (FDI) procedure:

o residual generation

#### o residual evaluation

- Evaluation of Gaussian residuals
  - o for parametric change in linear systems
  - o for small parametric change in nonlinear systems (local asymptotic approach to change detection)
- ullet Changes in the mean of a Gaussian vector  $\chi^2$ -tests

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# Basic formulas for the $\chi^2$ -tests

$$\mathrm{Iz} \sim \mathcal{N}(M\eta,\Sigma) \ \ \mathrm{I} = M^T \Sigma^{-1} M \ \ \eta = egin{bmatrix} \eta_a \ \eta_b \end{bmatrix} \ \ M = [M_a \ M_b] \ \ \mathrm{I} = egin{bmatrix} \mathrm{I}_{aa} \ \mathrm{I}_{ab} \ \mathrm{I}_{ba} \ \mathrm{I}_{bb} \end{bmatrix}$$

Fault detection (global test)

$$t = \mathbf{z}^T \Sigma^{-1} M (M^T \Sigma^{-1} M_a)^{-1} M_a^T \Sigma^{-1} \mathbf{z}$$

Fault isolation by sensitivity test

$$ilde{t}_a = \mathrm{z}^T \Sigma^{-1} M_a (M_a^T \Sigma^{-1} M_a)^{-1} M_a^T \Sigma^{-1} \mathrm{z}^{-1}$$

or equivalently

$$egin{array}{ll} ilde{\zeta}_a &= M_a^T \Sigma^{-1} \mathrm{z} \ ilde{t}_a &= ilde{\zeta}_a^T \mathrm{I}_{aa}^{-1} ilde{\zeta}_a \end{array}$$

# Advanced numerical computation of $\chi^2$ tests

for fault detection and isolation

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Gaussian residual evaluation —  $\chi^2$ -tests

Consider *m*-dimensional residual  $z \sim \mathcal{N}(M\eta, \Sigma)$ with  $M \in \mathbb{R}^{m \times n}$ ,  $\eta \in \mathbb{R}^n$ ,  $\Sigma \in \mathbb{R}^{m \times m}$ ,  $m \ge n$ .

Fault detection

$$H_0:\eta=0$$
 against  $H_1:\eta
eq 0$ 

Fault isolation for some partition  $\eta = \begin{bmatrix} \eta_a \\ \eta_b \end{bmatrix}$  $H_0: \eta_a = 0$  against  $H_1: \eta_a \neq 0$ 

These hypothesis testing problems lead to  $\chi^2$ -tests.

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then

Same as global test (M being replaced by  $M_a$ ).

Advanced numerical computation:

# Basic formulas of the $\chi^2$ -tests (contd.)

Fault isolation by min-max test

$$egin{array}{ll} ilde{\zeta}_a &= M_a^T \Sigma^{-1} \mathrm{z} \ ilde{\zeta}_b &= M_b^T \Sigma^{-1} \mathrm{z} \ ilde{\zeta}_a^* &= ilde{\zeta}_a - \mathrm{I}_{ab} \mathrm{I}_{bb}^{-1} ilde{\zeta}_b \ \mathrm{I}_a^* &= \mathrm{I}_{aa} - \mathrm{I}_{ab} \mathrm{I}_{bb}^{-1} \mathrm{I}_{ba} \ t_a^* &= ilde{\zeta}_a^* \mathrm{I}_a^{*-1} ilde{\zeta}_a^* \end{array}$$

Numerical difficulties: when the matrices to be inverted are badly conditioned, these basic formulas can lead to large numerical errors. It is thus important to develop advanced numerical algorithms.

Advanced numerical computation – Sensitivity test

 $\tilde{t}_a = \mathbf{z}^T \Sigma^{-1} M_a (M_a^T \Sigma^{-1} M_a)^{-1} M_a^T \Sigma^{-1} \mathbf{z}$ 

QR decomposition of  $\Gamma M_a$ :  $\Gamma M_a = Q_a R_a$  with  $Q_a^T Q_a = I$ ,

 $ilde{t}_a = \|Q_a^T \Gamma \mathbf{z}\|^2$ 

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## Advanced numerical computation – Global test

$$t = \mathbf{z}^T \Sigma^{-1} M (M^T \Sigma^{-1} M)^{-1} M^T \Sigma^{-1} \mathbf{z}$$

- $\bullet$  Use pseudo-inverse for  $\Sigma^{-1}$  if badly conditioned
- Compute t as a square :  $t = \|(M^T \Sigma^{-1} M)^{-\frac{1}{2}} M^T \Sigma^{-1} \mathbf{z}\|^2$
- Avoid the inverse involving M.

Proposed solution:

- let  $\Gamma = \Sigma^{-\frac{1}{2}}$  (with pseudo-inverse if necessary),
- QR decomposition of  $\Gamma M$ :  $\Gamma M = QR$  with  $Q^T Q = I$ ,

• Then

$$egin{aligned} t &= \mathbf{z}^T \Gamma Q R (R^T Q^T Q R)^{-1} R^T Q^T \Gamma \mathbf{z} \ &= \mathbf{z}^T \Gamma Q R (R^T R)^{-1} R^T Q^T \Gamma \mathbf{z} \ &= \| Q^T \Gamma \mathbf{z} \|^2 \end{aligned}$$

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# Advanced numerical computation – Minmax test

More computations are involved.

QR decompositions:

$$egin{aligned} \Gamma M_a &= Q_a R_a \ \Gamma M_b &= Q_b R_b \ I - Q_b Q_b^T) Q_a &= Q_c R_c \end{aligned}$$

then

 $t_a^* = \|Q_a^T \Gamma \mathbf{z}\|^2$ 

A non-trivial step for deriving the algorithm:

$$(I - Q_a^T Q_b Q_b^T Q_a) = Q_a^T (I - Q_b Q_b^T) (I - Q_b Q_b^T) Q_a$$

Remark: SVD can be used instead of QR decomposition.

# $\label{eq:aussian} \begin{array}{l} \textbf{A numerical example} \\ \text{Gaussian vector: } \dim(\textbf{z}) = 9, \dim(\eta) = 5, \dim(\eta_a) = 2. \\ \text{Condition number of } \Sigma: \ 3.4 \times 10^{10}. \\ \text{Histograms are based on 10000 random realizations.} \end{array}$





Advanced minmax test (solid line) and  $\chi^{\prime 2}(2,44.955)$  density function (dashed line).

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## Conclusion

- $\chi^2$ -tests are frequently used for residual evaluation.
- Advanced numerical algorithms can significantly improve the numerical accuracy of badly conditioned problems.

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