Subspace Instability Monitoring for Linear Periodically Time-Varying Systems
Ahmed Jhinaoui, Laurent Mevel, Joseph Morlier

To cite this version:

HAL Id: hal-01853135
https://hal.archives-ouvertes.fr/hal-01853135
Submitted on 2 Aug 2018

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L’archive ouverte pluridisciplinaire HAL, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d’enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.
Open Archive Toulouse Archive Ouverte (OATAO)

OATAO is an open access repository that collects the work of Toulouse researchers and makes it freely available over the web where possible.

This is an author-deposited version published in: http://oatao.univ-toulouse.fr/
Eprints ID: 6726


Any correspondence concerning this service should be sent to the repository administrator: staff-oatao@inp-toulouse.fr
Subspace Instability Monitoring for Linear Periodically Time-Varying Systems

Ahmed Jhinaoui ∗ Laurent Mevel ∗∗ Joseph Morlier ∗∗∗

Abstract: Most subspace-based methods enabling instability monitoring are restricted to the linear time-invariant (LTI) systems. In this paper, a new subspace method of instability monitoring is proposed for the linear periodically time-varying (LPTV) case. For some LPTV systems, the system transition matrices may depend on some parameter and are also periodic in time. A certain range of values for the parameter leads to an unstable transition matrix. Early warning should be given when the system gets close to that region, taking into account the time variation of the system. Using the theory of Floquet, some symptom parameter of stability- or residual- is defined. Then, the parameter variation is tracked by performing a set of parallel cumulative sum (CUSUM) tests. Finally, the method is tested on a simulated model of a helicopter with hinged blades, for monitoring the ground resonance phenomenon.

Keywords: Helicopter dynamics, Time-varying systems, Periodic motion, Resonance, Subspace methods, Statistical inference, Fault detection, Stability limits

1. INTRODUCTION

Instability monitoring is currently the subject of extensive research activities motivated by an increasing requirement on the design of highly reliable control systems, for numerous applications such as civil engineering and aeronautics. Under some assumptions, such structures can be modeled by a linear time-invariant (LTI) model. The goal is to detect any anomalous behavior on these structures, and to alarm the user before any dysfunction or destruction occurs. There is a large amount of literature on the subject of instability monitoring, which has been handled with different approaches (see Angeli and Chatzinikolaou [2004] for details). One particular method, namely the subspace-based method, consists in comparing the characteristics of a system at a reference state with a subspace matrix given by new data corresponding to an unknown, possibly different state, as explained in Basseville et al. [2000]. To check whether a change has occurred or not, a quasi-distance between the two states - called residual- is defined. Then, a statistical test decides if this residual is significantly different from zero. If some threshold is exceeded, the system has changed with respect to the reference. An overview of the different approaches of this general approach can be found in Basseville et al. [2000].

The subject of this paper is the extension of this approach to periodically time-varying (varying, even for fixed internal command’s values) systems such as wind turbines and rotor systems, replacing the residual in Mevel et al. [2005] by a robust one considered in Döhler and Mevel [2011]. To the best of the knowledge of the authors, the bibliography on subspace methods for LPTV systems is not abundant. For instance, in Verhaegen and Yu [1995], some attempts have been carried out in subspace-based identification. Some other works have dealt with recursive tracking of periodic subspaces, as in Buzzi et al. [2003]. Otherwise, Bayesian filtering such as Kalman and particle filters, or robust and adaptive observers are also used. Two key features motivate the study reported herein:

- A simple, necessary and sufficient criterion of stability can be extracted from periodic data, using the theory of Floquet (Dacunha and Davis [2009]). Therefore, a simple residual based on this criterion can be built
- A set of time-invariant data subsequences that have the same time-varying behavior can be found for such system is labeled as LTI, even if it depends on those internal commands (this class of systems is called linear parameter-varying (LPV) in control theory, but it is still considered time-invariant for each fixed parameter). This assumption holds since for each command’s value, data has a time-invariant behavior, and since the command varies slowly as a step function, generally. The problem will be to detect a significant change of the structural characteristics leading to instability as those commands fluctuate and some system eigenvalue starts to cross the Nyquist circle. This problem has been solved for aircraft flutter monitoring in Mevel et al. [2005].

This work was supported by the European project FP7-NMP CP-IP 213968-2 IRIS. The authors acknowledge Leonardo Sanches for insightful discussions and comments.
periodic systems, as outlined in Meyer and Burrus [1975], which makes it possible to apply a detection algorithm similar to the classical time-invariant one (Mevel et al. [2005]), for each of these sequences

Once the criterion of stability is found, a set of residuals, corresponding to each time-invariant subsequence, is defined. Then, parallel statistical tests are performed to decide if an eventual change in the system characteristics has occurred. The statistical test used herein is the cumulative sum (CUSUM) because it is adequate for online implementation and for the detection of the instant of change (see Basseville and Nikiforov [1993]). The paper is organized as follows: in Section 2, the essential elements of the subspace methods for identification and instability monitoring are recalled. Then, Section 3 is devoted to the design of the new LPTV-extended method of instability monitoring. Finally, in Section 4 an illustrative simulation case is studied in order to test the efficiency of the suggested method.

2. SUBSPACE-BASED METHODS FOR LTI SYSTEMS

2.1 Subspace Identification

Consider the discrete time model, describing a system in the state space form:

\[ z_{k+1} = F z_k + w_k \]
\[ y_k = H z_k + v_k \]

with the state vector \( z \in \mathbb{R}^n \), the output vector \( y \in \mathbb{R}^r \), the state transition matrix \( F \in \mathbb{R}^{n \times n} \) and the observation matrix \( H \in \mathbb{R}^{r \times n} \). The vectors \( w \) and \( v \) are unmeasured noises, assumed to be white Gaussian. The eigenstructure of (1) is given by the roots (\( \lambda, \phi \)) of the equations, below:

\[ \det(F - \lambda I) = 0, \quad F \phi = \lambda \phi \]

Let \( p \) and \( q \) be chosen parameters such that \( \min\{p, q\} \geq n \). From the output data \((y_k)\), a Hankel matrix \( H_{p,q} \in \mathbb{R}^{(p+1)\times(q+1)} \) is built:

\[ H_{p,q} = \begin{bmatrix} R_1 & R_2 & \cdots & R_q \\ R_2 & R_3 & \cdots & R_{q+1} \\ \vdots & \vdots & \ddots & \vdots \\ R_{p+1} & R_{p+2} & \cdots & R_{p+q} \end{bmatrix} \]

where the covariances of the output data write \( R_k = E(y_k y_k^T) \) and \( E \) is the expectation operator. When the number of data \( N \) goes to infinity, the approximations below hold: \( \hat{R}_k = \frac{1}{N} \sum_{i=1}^{N} y_i y_i^T \) and \( \hat{H}_{p,q} = \frac{1}{N} \sum_{k=q}^{N-p} \hat{y}_k \hat{y}_k^T \), where \( \hat{y}_{k+} = (y_{k+1} \ldots y_{k+p})^T \) and \( \hat{y}_{k-} = (y_{k-p} \ldots y_{k-1})^T \). The Hankel matrix can be factorized as below (see Benveniste and Fuchs [1985]):

\[ H_{p,q} = O_p C_q \]

where \( O_p = \begin{bmatrix} H & H F & \cdots & H F^{p-1} \end{bmatrix} \) and \( C_q = \begin{bmatrix} FG, F^2 G, \cdots, F^q G \end{bmatrix} \) and \( G = \sqrt{\sum_{k=q}^{N-p} y_k y_k^T} \). Therefore, the observability matrix \( O_p \) is obtained from a thin singular value decomposition (SVD) of the matrix \( H_{p,q} \) and its truncation at the desired order \( n \) (Basseville et al. [2000]):

\[ H_{p,q} = U \Delta V^T = [U_1 \ U_2] \begin{bmatrix} \Delta_1 & 0 \\ 0 & \Delta_2 \end{bmatrix} \begin{bmatrix} V_1^T \\ V_2^T \end{bmatrix} \]

with \( U_1 \) the left subspace of \( H_{p,q} \) found in the \( n \) first column of \( U \), and \( \Delta_1 \) the \( n \) upper singular values of \( \Delta \). The observation matrix \( H \) is found in the first block-row of \( O_p \). To get the transition matrix \( F \), the shift invariance property of \( O_p \) is used in resolving the least square solution of (Basseville et al. [2007]):

\[ O_p^T F = O_p^\dagger \]

where:

\[ O_p^\dagger = \begin{bmatrix} H & HF & \cdots & H F^{p-1} \end{bmatrix} \]

2.2 Subpace Instability Monitoring

In this section, the statistical subspace-based instability monitoring from Basseville et al. [2007] and Mevel et al. [2005] is recalled, where a residual function for change detection is associated with the subspace identification described in the previous section. This function, or residual, compares the system parameter \( \theta \) of a reference with a block Hankel matrix computed on new data \((y_k)_{k=1\ldots N}\) corresponding to an unknown, possibly different parameter \( \theta \). To decide whether a significant change has occurred or not, a local approach is used to decide between two hypotheses:

\[ H_0 : \theta = \theta_0 \quad \text{and} \quad H_1 : \theta = \theta_0 + \delta \theta / \sqrt{N} \]

where \( \delta \theta \) is unknown but fixed. Let \( K \) be a left kernel of the Hankel matrix at the reference \( H_{p,q}^0 , \) such that:

\[ K^T (\theta_0) H_{p,q}^0 = 0, \quad K^T (\theta_0) K (\theta_0) = I \]

To check whether new data agree with the reference state corresponding to \( \theta_0 \), the residual function below is introduced in Basseville et al. [2000]:

\[ \mathcal{X}_N (\theta_0) = \sqrt{N} \ \text{vec} (\hat{K}^T (\theta_0) H_{p,q}) \]

where \( H_{p,q} \) is the Hankel matrix built with new data from the current parameter \( \theta \), possibly different from \( \theta_0 \). From now on, we will use another residual that is robust to noise changes, recently suggested in Döhler and Mevel [2011]:
\[ \zeta_N(\theta_0) = \sqrt{N} \text{vec}(K^T(\theta_0)U_1) \]  
(11)

where \( K \) is the left kernel of the left subspace \( U_0^T \) of \( H_{p,q}^\theta \) at the reference, and \( U_1 \) the left subspace of Hankel matrix \( H_{p,q} \) built on the current data. Let \( J(\theta_0) \) be the matrix of partial derivatives of the vectorized residual with respect to the vector of parameters (Mevel et al. [2005]) and \( \Sigma(\theta_0) \) is the residual covariance matrix, which can be estimated as an empirical sum (Basseville et al. [2000]). The matrices \( \Sigma(\theta_0) \) and \( J(\theta_0) \) associated to the residual in (11) are independent of the possibly time varying noise properties (Döhler and Mevel [2011]). If \( \Sigma(\theta_0) \) is positive definite and assuming \( \theta \) as in (9), the central limit theorem (CLT) insures that the residual \( \zeta_N(\theta_0) \) in (11) is asymptotically Gaussian distributed (Döhler and Mevel [2011]):

\[ \zeta_N(\theta_0) \rightarrow N(J(\theta_0)\delta\theta, \Sigma(\theta_0)) \]  
(12)

which implies that the mean of \( \zeta_N(\theta_0) \) converges to 0 only under \( H_0 \) (i.e. \( \delta\theta = 0 \)). In other words, detecting if the eigenstructure has changed from the reference is equivalent to detecting a change in the mean of \( \zeta_N(\theta_0) \).

In order to detect the direction of the change, a normalized residual \( \bar{\zeta}_N(\theta_0) \) is introduced, such that:

\[ \bar{\zeta}_N(\theta_0) = J(\theta_0)\Sigma^{-1}(\theta_0)\zeta_N(\theta_0), \]  
(13)

which leads to the normal distribution:

\[ \bar{\zeta}_N(\theta_0) \rightarrow N(\Sigma(\theta_0)\delta\theta, \Sigma(\theta_0)) \]  
(14)

where: \( \Sigma(\theta_0) = J(\theta_0)\Sigma^{-1}(\theta_0)J(\theta_0) \). This covariance matrix is positive definite. Therefore, a positive (resp. negative) change in the normalized residual \( \bar{\zeta}_N(\theta_0) \) reflects a positive (resp. negative) change in \( \delta\theta \). A recursive decision function, or residual, is introduced in order to design an on-line monitoring algorithm:

\[ Z_k = J(\theta_0)^T\Sigma(\theta_0)^{-1} \text{vec} \left( K^T(\theta_0)U_{1,k} \right) \]  
(15)

where \( U_{1,k} \) is the current left subspace of the Hankel matrix at the \( k \)-th sample data \( y_k \), obtained by an update of the SVD. Based on the recursive residual in (14) and considering that the \( Z_k \)'s are independent Gaussian which describe themselves a change in \( \delta\theta \) by a change in their mean, a commonly used CUSUM test (Basseville and Nikiforov [1993]) is applied. In general, only the part \( \lambda \) of \( \delta\theta \) changes with respect to time. The eigenvectors are assumed to be constant, considering the small displacement hypothesis (SDH). Now, denote \( \rho \) as the norm of one of the eigenvalues \( \lambda \)'s of \( F \) and notice that when one of the \( \rho \)'s increases to 1, the system goes toward instability (Basseville and Nikiforov [1993]). The CUSUM test described below allows to detect an increase in any component of the parameter \( \theta \) by using as Jacobian matrix the corresponding submatrix of \( J(\theta_0) \) : the sensitivity \( J(\theta_0) \) is replaced in (14) by the matrix \( J(\theta_0) \) corresponding to the sensitivity with respect to \( \rho \) at \( \rho = \rho_0 \): \( S_k(\rho_0) = \Sigma(\rho_0)^{-1/2} \sum_{j=q}^{k} Z_j(\rho_0), \) \( T_k(\rho_0) = \min_{q \leq j \leq k} S_j(\rho_0) \) and \( g_k(\rho_0) = S_k(\rho_0) - T_k(\rho_0). \) The two hypotheses \( H_{0,k} \) and \( H_{1,k} \) to decide between, at each instant \( k \), are now:

\[ \begin{aligned} H_{0,k} : & \quad g_k(\rho_0) \approx 0 \\ H_{1,k} : & \quad g_k(\rho_0) > \epsilon \end{aligned} \]  
(16)

where \( \epsilon \) is some empirically tuned threshold (Mevel et al. [2005]) that allows to detect only the significant changes. If this threshold is exceeded, the test reacts and the current data are describing a new value for the parameter \( \rho > \rho_0 \). The test described above is applied to all the norms of the eigenvalues \( (\lambda_i)_1 \leq n \) and when a change is detected in one of the \( \rho_i \), the system is considered to be unstable.

### 3. Subspace Instability Monitoring in LPTV Case

Linear periodically time-varying systems are encountered in many different fields. Some of the most relevant applications that involve periodic behaviors are rotor systems such as helicopters and wind turbines, satellite control of attitude or also in communications. This class of systems is considered as an intermediate class bridging the time-invariant case to the time-varying one. For the latter class, the stability analysis is generally based on complex algebraic-analytic tools (see Bourles and Bogdan [2011] for details). Finding a criterion of stability is a crucial step in subspace instability monitoring, because a residual based on this criterion has to be built and then tracked by the statistical test presented in the last section. It seems difficult to get a simple criterion for time-varying systems in general. Hopefully, there exist specific methods for periodic systems that give relatively simple criteria about stability. One of these methods is the modal analysis using the transformation of Floquet, described hereafter.

#### 3.1 Transformation of Floquet

Let consider the continuous LPTV system below, with a period \( T \):

\[ \begin{aligned} \dot{x}(t) &= A(t)x(t) + w(t), \\ y(t) &= Cx(t) + v(t) \end{aligned} \]  
(17)

with \( x \in \mathbb{R}^n \) the state vector, \( A \in \mathbb{R}^{n \times n} \) the state matrix, \( y \in \mathbb{R}^r \) the output vector and \( C \in \mathbb{R}^{r \times n} \) the observation matrix. The vectors \( w \) and \( v \) are two additive noises assumed to be white Gaussian. The idea of the Floquet transformation is to replace this system by an equivalent autonomous (i.e. the matrix of transition is no more function of time) one.

**Theorem 1.** If \( A \) is continuous in time- or at least piecewise continuous- and an initial condition \( x(t_0) = x_0 \) is fixed, then a solution of \( \dot{x}(t) = A(t)x(t) \) is guaranteed to exist. Let \( \Phi(t) \) be the matrix whose \( n \) columns are \( n \) linearly independent solutions, \( \Phi(t) \) is known as the Fundamental Transition Matrix (FTM) and \( \Phi(t) = A(t)\Phi(t) \). Let \( \Phi(t) \Phi(T) \) be the matrix whose \( n \) columns are \( n \) linearly independent solutions, \( \Phi(t) \) is known as the Fundamental Transition Matrix (FTM) and \( \Phi(t) = A(t)\Phi(t) \). Let \( \Phi(t) \Phi(T) \) be the matrix whose \( n \) columns are \( n \) linearly independent solutions, \( \Phi(t) \) is known as the Fundamental Transition Matrix (FTM) and \( \Phi(t) = A(t)\Phi(t) \).

**Proof.** see Dacunha and Davis [2009]

**Corollary 2.** (Floquet Transformation) The value of the fundamental matrix at \( t = T \) is called the Monodromy Matrix.

\[ Q = \Phi(T) \]  
(18)

Let \( R = \frac{1}{T} \log(Q) \) and \( x(t) = \Phi(t)e^{-RT}z(t) \). Then, the first-order ordinary differential equation above can be transformed into the equivalent equation:

\[ \dot{z}(t) = Rz(t) \]  
(19)
The equation of observation for the new variable $z$ is

$$y(t) = C'(t)z(t)$$

where $C'(t) = C\Phi(t)e^{-RT}$ and $C'(t + T) = C\Phi(t + T)e^{-RT} = C\Phi(t)e^{-RT} = C'(t)$. Therefore, any system that writes as in (16) can be transformed into an equivalent autonomous system with a periodic matrix of observation:

$$
\begin{align*}
\dot{z}(t) &= Rz(t) + (\Phi(t)e^{-RT})^{-1}w(t) \\
y(t) &= C'(t)z(t) + v(t), \quad C'(t + T) = C'(t), \forall t
\end{align*}
$$

According to Floquet theory, the continuous system (19) is stable if and only if the real parts of eigenvalues of $R$ are negative or, similarly, if the norms of the eigenvalues of $Q$ in (17) are inferior to one. Let consider the discretized form of (19), at a sampling rate $\tau$ (where $T$ is assumed to be a multiple of $\tau$) (Ma and Iglesias [2002]):

$$
\begin{align*}
z_{k+1} &= Fz_k + \Gamma kw_k \\
y_k &= Hz_k + v_k
\end{align*}
$$

The discretized monodromy matrix $F = e^{RT}$, the discretized matrix of observation $H = C'(k\tau)$ and $\Gamma_k = \int_{k\tau}^{(k+1)\tau} e^{-\gamma T}d\gamma$ are periodic. The discrete period is $T_d = \frac{T}{\tau}$.

### 3.2 Residuals Generation

As outlined in Meyer and Burrus [1975], the data $(y_k)$ have different varying dynamics in the periodic case. However, the subsequences $(y_{k0+T_d})_{k\in\mathbb{N}}$ and $(z_{k0+T_d})_{k\in\mathbb{N}}$ are shown to have time-invariant behaviors for any $k_0 \in \mathbb{N}$. A total of $T_d$ different time-invariant subsequences exists. Let the eigenstructure below be the parameter function of one of these subsequences (denoted the $j$-th subsequence, with $j \in [1, T_d]$):

$$
\theta^{(j)} = \begin{pmatrix}
\Lambda \\
vec(\Phi_0) \\
vec(\Phi_1) \\
\vdots \\
vec(\Phi_{N-1})
\end{pmatrix}
$$

where $\Lambda$ is the vector of the eigenvalues $\lambda_i$ of $F$ and the mode shapes $\Phi$ are the observed eigenvectors of $F$, $\Phi_j = [\phi_{j0}, \phi_{j1}, \ldots, \phi_{j,N-1}]$ with $\Phi_0 = \phi_0$. The condition in the discrete form is that the eigenvalues of $F$ are in the Nyquish circle. The Hankel matrices are built using the time-invariant subsequences as described hereafter.

**Lemma 3.** For any $j \geq q$ and if $(NT_d + p)$ data samples are available, the $j$-th Hankel matrix $H^{(j)}_{p,q}$ is defined as:

$$
H^{(j)}_{p,q} = \frac{1}{N} \sum_{i=0}^{N-1} \mathcal{Y}^+_{j+iT_d} \mathcal{Y}^-_{j+iT_d}
$$

This matrix can be factorized as in (4) to the product:

$$
H^{(j)}_{p,q} = O^{(j)}_{p,q} C^{(j)}_{p,q}
$$

where $O^{(j)}_{p,q}$ is the observability matrix for the $j$-th subsequence, such that:

$$
O^{(j)}_{p,q} = \left[ H^T_j \ H^T_{j+1} \ H^T_{j+p} \right]^T
$$

Notice that unlike the LTI case, the observation matrix $H_{j+i}$ is varying with $i = 1, \ldots, p$.

**Proof.** see Jhinaoui et al. [2012]

**Fact 4.** For notation simplicity, $T$ is assumed to be a multiple of $\tau$. In general, this is not the case and the time-invariant subsequences are the ensembles $(y_{[\tau]}(i))$, and the data $Y^+_{j+iT_d}$ and $Y^-_{j+iT_d}$ are replaced by $Y^+_{[\tau]_{j+iT_d}}$ and $Y^-_{[\tau]_{j+iT_d}}$ (where $[\ ]$ is the floor operator), in order to get the sum for approximately the same subsequence.

The observability matrix can be obtained, similarly to Section 2, from a thin singular value decomposition (SVD) of the Hankel matrix $H^{(j)}_{p,q}$:

$$
H^{(j)}_{p,q} = U_1^{(j)} U_2^{(j)} \begin{pmatrix}
\Delta_1^{(j)} & 0 \\
0 & \Delta_2^{(j)}
\end{pmatrix} \begin{pmatrix}
V_1^{(j)} \\
V_2^{(j)}
\end{pmatrix}^T
$$

Writing $O^{(j)}_{p,q}$ in the modal basis gives:

$$
\mathcal{O}^{(j)}_{p} = U_1^{(j)} (D^{(j)})^{1/2} \begin{pmatrix}
\Phi^T_j \ (\Phi_{j+1} D) \\
\cdots \\
(\Phi_{j+p} D^p)
\end{pmatrix}^T T
$$

Then, a left kernel $K^{(j)}$ of the left subspace $U_1^{(j)}$ of $H^{(j)}_{p,q}$ is deduced:

$$
(K^{(j)})^T U_1^{(j)} = 0, \quad \forall j \in [1, T_d]
$$

The $T_d$ equations in (28) are satisfied if current output data describe well the reference parameters $\theta^{(j)}_0$. These functions are the candidates to be the residuals that compare current data to reference parameters. In the periodic case, there are $T_d$ residuals, one for each of the $T_d$ time-invariant subsequences. At an instant $k$, these residuals write in recursive forms $\forall j \in [1, T_d]$, as in (14):

$$
Z^{(j)}_k = (J^{(j)}(\theta^{(j)}_0)) T (\Sigma^{(j)}(\theta^{(j)}_0))^{-1} vec(K^{(j)})^T U_1^{(j)}
$$

where $K^{(j)}$ is the left kernel at the reference $\theta^{(j)}_0$, $U_1^{(j)}$ the left subspace update of the Hankel matrix $H^{(j)}_{p,q}$, when the $k$-th data sample of the $(j)$-th subsequence is available, and $J^{(j)}(\theta^{(j)}_0)$ and $\Sigma^{(j)}(\theta^{(j)}_0)$ are the residual’s sensitivity and covariance matrices as in Döhler and Mevel [2011].

### 3.3 Parallel CUSUM Tests

Let $\rho_0$ be the norm of one of the eigenvalues contained in $\Lambda$. The goal herein is to decide whether the value of $\rho_0$ has increased. For each time-invariant subsequence, the hypotheses to decide between at the time sample $k$ are:
the system is periodic of period $T$.

To summarize the algorithm:

$$S_k^{(j)}(\rho_0) = \sum_{i=1}^{k} \mathcal{Z}_i^{(j)}(\rho_0)$$

$$T_k^{(j)}(\rho_0) = \min_{q=1}^{N} S_k^{(j)}(\rho_0)$$

$$g_k^{(j)}(\rho_0) = S_k^{(j)}(\rho_0) - T_k^{(j)}(\rho_0)$$

$\mathcal{Z}_i^{(j)}(\rho_0)$ is the recursive residual with respect to $\rho_0$ and replacing, in (29), the sensitivity $\mathcal{J}^{(j)}(\theta_0)$ by the sensitivity $\mathcal{J}^{(j)}(\rho_0)$. Notice that when the monitoring starts, no information is available about the relation in time between the identified reference and the current data. In other words, if the monitoring starts at $t = t_0$ (with $t_0 \geq 0$) and $(NT_d+p)$ data are available, it is not known to which kernel $K^{(j)}$ the Hankel matrix $\mathcal{H}_{p,q}(t_0)$ corresponds, because the phase of identification and the phase of monitoring may have not the same time origin. The current data is synchronized with the reference parameter kernel (denoted $K^{(j)}$) as follows:

$$K^{(j)} := \arg\min_{j=1,T_d} \left( \left\| (K^{(j)})^T \mathcal{H}_{p,q}(t_0) \right\| \right)$$

To summarize the algorithm:

- using the identification algorithm described in Jhi-nou et al. [2012], a set of $T_d$ kernels $K^{(j)}$, corresponding to the $T_d$ time-invariant subsequences is computed at a fixed reference $\theta_0 = (\theta_0^{(j)})_{j=1,\ldots,T_d}$
- the Jacobians and the covariances matrices are computed (see Döhler and Mevel [2011])
- the importance of the monitoring is the two lateral displacements $X$ and $Y$, and the lag angular motions $\phi_k$ for each of the $N_b$ blades. The equations of motion of this helicopter’s mechanical model system writes:

$$M(t)\ddot{X}(t) + C(t)\dot{X}(t) + K(t)X(t) = 0$$

The mass, the damping and the stiffness matrices $M$, $C$ and $K$ are periodic of period $T = \frac{2\pi}{\tau}$ and $X = [x \ y \ \phi_1 \ \phi_2 \ \cdots \ \phi_{N_b}]^T$. Let $X = [X^T \ \dot{X}^T]^T$, then (33) can be written in a state space form:

$$\dot{X}(t) = A(t)X(t)$$

Where the periodic state transition matrix writes:

$$A(t) = \begin{bmatrix} 0 & I \\ -M^{-1}(t)K(t) & -M^{-1}(t)C(t) \end{bmatrix}$$

The equation of observation is $y(t) = CX(t)$ where $C = [0 \ I]$. The numerical values used for simulation are those reported in Byers and Gandhi [2009] and $N_b = 4$.

4.2 Simulation

Using Matlab, time series data are simulated from the mechanical model above with a sampling rate $\frac{1}{2} = 50Hz$. The scenario consists in simulating an angular velocity’s acceleration from $\Omega_0 = 3.1rad/s$ to $\Omega_{final} = 4.5rad/s$ (close to resonance) with a step of 0.1rad/s. For each value of $\Omega$, 1000 samples are simulated and the eigenvalues of $F$
in (20) are computed. The imaginary parts of these eigenvalues are negligible. Therefore, the real parts \( \rho_1 \cdots \rho_n \), which are positive, are close approximations of the norms of these eigenvalues. The evolution of the \( \rho_i \)'s with respect to airspeeds \( \Omega \) is plotted in Fig. 2. The resonance onset can be observed when one of the \( \rho_i \)'s exceeds 1. Notice that the \( \rho_i \)'s vary very close to instability.

4.3 Results

At the chosen reference corresponding to \( \Omega_0 = 3.1 \text{rad/s} \), the system is identified on a large data set from the subspace identification algorithm described in Jhinaoui et al. [2012]. The kernels, Jacobians and covariance matrices of the \( T_{\Omega_0} = 102 \) time-invariant data subsequences are computed at this time (Döhler and Mevel [2011]). At the beginning of the monitoring phase, the Hankel matrix computed on current data is synchronized with respect to its proper reference kernel (as given in (32)). This synchronization is performed using (32) whose minimum is plotted in Fig. 3. The x-axis represents the index of the reference kernels, and the y-axis the value of the cost in equation (32). It corresponds to the correct phase (as defined by the simulation) at an index equal to 50. Once the synchronization is done, the monitoring phase begins. For each of the \( T_{\Omega} \) time-invariant subsequences, a CUSUM test is started. The number of tests \( T_{\Omega} \) is decreasing with respect to the angular velocity \( \Omega \) which means that some time-invariant subsequences have vanished. At \( \Omega_{\text{mat}} \), only 70 subsequences (then, 70 parallel tests) will remain. A choice of \( \epsilon = 1000 \) was taken based on the fluctuation of \( \rho \) whose minimum is plotted in Fig. 3.

Fig. 2. Real parts \( \rho_1 \) to \( \rho_6 \) vs. angular velocity (N.B: \( \rho_1 \simeq \rho_2 \))

Fig. 3. Cost function vs. indexes of reference kernels

The problem of instability monitoring for linear periodically time-varying systems is addressed. The most challenging point is to define a simple criterion of stability for these LPTV systems. This problem is solved using the Floquet theory. Then, new instability monitoring tests are developed, similarly to the time-invariant case. The suggested method is successfully tested on simulation data of a helicopter model. Current works are carried out to apply the same method to real industrial applications.

5. CONCLUSION

The problem of instability monitoring for linear periodically time-varying systems is addressed. The most challenging point is to define a simple criterion of stability for these LPTV systems. This problem is solved using the Floquet theory. Then, new instability monitoring tests are developed, similarly to the time-invariant case. The suggested method is successfully tested on simulation data of a helicopter model. Current works are carried out to apply the same method to real industrial applications.

REFERENCES


