Low-Computational Cost Estimation Algorithm for Adaptive Optics Systems *

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Abstract: Astronomical images received by ground-based telescopes are affected by atmospheric turbulence leading to optical deformations. Hence, adaptive optics systems have been developed as a way to compensate for these optical deformations before images arrive to the telescope high resolution camera. The advent of very large telescopes leads to adaptive optics systems requiring a large computational load and leading to an important time delay that deteriorates performances. Through this paper, a novel solution is explored to overcome the high computational cost of the estimation process while still attaining good performances. The aim of the proposed method is to synthesize a reduced-order filter gain using a turbulence model with large number of Zernike modes. Since the algorithm does not synthesize a full-order gain, the computational cost is significantly reduced for the synthesis and the estimation.

Keywords: Large scale optimization problems; Observers for linear systems; Linear multivariable systems; Time-invariant systems; Industrial applications of optimal control.

1. INTRODUCTION

The light traveling from remote places in the universe to the earth can be considered as a flat wave. However, once it enters in the atmosphere, a multitude of air layers slow down the light beams before arriving to the telescope high resolution camera. These delays cause a change in the phase of the image that severely limits the resolution of the obtained images.

To overcome the deterioration of the resolution, some ground-based telescopes include an adaptive optics system (AOS) to compensate for the deformations due to atmospheric turbulence. AOSs are generally composed of a wavefront sensor (WFS), a real-time computer (RTC) and a deformable mirror (DM). As shown in Fig. 1, the deformed wavefront arrives to the WFS, which gives an approximation of the shape of the wavefront surface. Then, the RTC computes the input signal applied to the actuators of the DM in order to change its form and reproduce the wavefront surface.

Since the wavefront surface is rapidly changing, the system must be able to recalculate, as fast as possible, the input signal applied to the DM whose dynamics is generally neglected. As new adaptive optics (AO) projects emerge, the size of the DM increases to improve the resolution (European Extremely Large Telescope is equipped with a 42m diameter mirror). The estimation of atmospheric turbulence is one of the principal keys to this improvement. However, in linear formulation, the only way to ameliorate spatial information on atmospheric turbulence is to increase the order of the estimation model. Thus, the number of computations involved grows to estimate precisely the wavefront surface. Hence, the aim of this paper is to present a procedure that allows a good estimation of the wavefront surface without compromising the general performances of the system by heavy computations.

In order to use an optimal linear quadratic regulator (LQR), we need to know the value of turbulence at each time. Since turbulence can not be measured, it can only be estimated. Different authors have proposed to use an adaptive filter (Gibson et al. (1999)) or a Kalman filter (Le Roux (2003); Beghi et al. (2008); Paschall and Anderson (1993); Petit et al. (2008); Fedrigo et al. (2009); Kulcsár et al. (2006); Piatrou and Roggermann (2007)), which according to separation principal corresponds to the $H_2$ compensator. Since the considered model is linear and

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time-invariant, it is common to synthesize an asymptotic Kalman filter that can be calculated offline. The asymptotic Kalman filter gain is easily found thanks to algebraic Riccati equations (ARE), see Anderson and Moore (1990).

However, the high number of estimated states leads to a larger number of calculations that increase the time delay of the system and possibly deteriorate the overall performances. Also, the numerical solution of ARE for large-scale model generally induces numerical errors. Thus, the proposed solution exploits a novel way to consider a high number of Zernike modes for reduced order filter gain. Subsequently, the latter filter reduces computations and leads to good performances. The solution is obtained by introducing structure constraints on the filter gain. Therefore, the use of ARE is no longer possible and it is replaced with an algorithm based on the gradient method given in Apkarian et al. (2008), to iteratively obtain a filter gain satisfying some constraints. The filter gain is synthesized with a specific structure to avoid futile computations that have not a strong influence.

The paper is organized as follows. Section 2 provides an insight on the main elements of the AOSs as well as their associated model. The main result is given in Section 3 where the synthesis procedure of the estimator is presented. In Section 4, simulation results show the efficiency of the proposed solution. Some concluding remarks and perspective works are given in Section 5.

2. ADAPTIVE OPTICS SYSTEM

A classical AO closed loop is shown on Fig. 2. The residual phase \( \phi_{\text{res}} \) is the difference between the atmospheric phase \( \phi_{\text{tur}} \) and the correction phase \( \phi_{\text{cor}} \). In AOSs, minimizing the variance of the residual phase maximizes the performances of the system (Kulcsár et al. (2006)).

In the next subsections, we consider the AOS model proposed by Le Roux (2003)) that is used for the estimation of atmospheric turbulence.

2.1 Turbulence and Zernike polynomials

The model presented by Le Roux considers a first-order AR process:

\[
\phi_{\text{tur}}(k + 1) = A_{\text{tur}}\phi_{\text{tur}}(k) + v(k),
\]

where \( \phi_{\text{tur}} \in \mathbb{R}^n \) is the turbulent phase expressed in the Zernike base, \( A_{\text{tur}} \in \mathbb{R}^{n \times n} \) is the evolution matrix that is diagonal and \( v \in \mathbb{R}^n \) is a zero-mean white gaussian noise with covariance matrix \( \Sigma_v \in \mathbb{R}^{n \times n} \).

The Zernike base is a set of polynomials that allows to describe the optical aberrations produced on a lens. This base is used to characterize the effects induced by atmospheric turbulence on the image phase. The polynomials vary accordingly to the radial order \( \alpha \in \mathbb{N} \) and the azimuthal order \( \beta \in \mathbb{N} \) as expressed in the following equations (Wyant and Creath (1992)):

- for \( \beta \neq 0 \):
  \[
  \begin{cases}
  i \text{ even}, & Z_i = R_\alpha^\beta(r) \cos \beta \theta, \\
  i \text{ odd}, & Z_i = R_\alpha^\beta(r) \sin \beta \theta,
  \end{cases}
  \]

- for \( \beta = 0 \):
  \[
  Z_\iota = R_\alpha^0(r),
  \]

where \( 0 \leq r \leq 1 \) and \( 0 \leq \theta < 2\pi \) are polar coordinates and:

\[
R_\alpha^\beta(r) = \sum_{s=0}^{\alpha-\beta} \frac{(-1)^s(2\alpha - \beta - s)!}{s!(\alpha - s)!(\alpha - \beta - s)!} r^{2\alpha-2s-\beta},
\]

with \( \beta \leq \alpha \).

Although the first 14 Zernike modes, excluding the mode zero, already describe 92% of atmospheric turbulence effects (Bokern (1990)), we need to consider an infinite number of Zernike polynomials to describe the turbulence. With the advent of very large telescopes, the DM allows to improve atmospheric turbulence attenuation. However, this latter fact is conditioned to an increasing number of Zernike modes in the turbulence model (1). We refer the reader to Le Roux (2003) for more details on Zernike polynomials and the model of atmospheric turbulence.

2.2 Wavefront sensor

The WFS gives an approximation of the wavefront surface. The most commonly used WFS is the Shack-Hartmann WFS, which is composed of an array of micro-lenses that focus the light arriving on them into a CCD camera, as shown in Fig. 3. The distances between the projected light spots, resulting from the incoming wavefront, and their respective theoretical centers, resulting from a plane wavefront, are measured. These data are used to calculate the mean slopes of the wavefront at some given points. As the WFS measures the residual phase, we may consider that there are just small changes in the phase. Thus, we can consider the linear measurement equation:

\[
y(k) = D (\phi_{\text{tur}}(k-1) - \phi_{\text{cor}}(k-1)) + w(k),
\]

\[
= D \frac{\phi_{\text{res}}(k-1)}{\phi_{\text{res}}(k-1)} + w(k),
\]

where \( D \in \mathbb{R}^{p \times n} \) is the matrix relating the slopes of the wavefront surface to the measures of the WFS and \( w \in \mathbb{R}^p \) is a zero-mean white gaussian noise with covariance matrix \( \Sigma_w \in \mathbb{R}^{p \times p} \) introduced by the sensor.

2.3 Deformable mirror

The DM aims to reproduce the estimated wavefront in order to make the residual phase as small as possible. Although, there are different types of DM, we consider the Stacked-Actuator Mirrors (SAM) that are the most commonly used along with the Shack-Hartmann WFS.

The SAM is made of piles of micro-actuators fixed to a reflecting surface. When a voltage is applied to one of these piles of actuators, they change their size and hence the
shape of the reflecting surface at the point where they are stacked to.

The dynamics of the SAM for the actual telescopes can be neglected since its response is in general faster than the sampling time of the WFS (Le Roux (2003)). Hence, we may write the following linear equation:

$$\phi_{cor}(k) = Nu(k-1), \quad (6)$$

where $u \in \mathbb{R}^m$ is the control input vector and $N \in \mathbb{R}^{n \times m}$ is the influence matrix relating the voltage inputs to the mirror surface deformation.

### 2.4 Space state representation

Having all the equations describing the system, the state-space representation given by Le Roux (2003) is used. This representation considers a delay introduced by the estimation of the atmospheric turbulence and the computation of the control laws, as well as the integration time of the WFS:

$$\begin{bmatrix} \phi_{tur}(k+2) \\ \phi_{tur}(k+1) \\ \phi_{tur}(k) \\ u(k) \end{bmatrix} = \begin{bmatrix} A_{tur} & 0 & 0 & 0 \\ I_n & 0 & 0 & 0 \\ 0 & I_n & 0 & 0 \\ 0 & 0 & I_m & 0 \end{bmatrix} \begin{bmatrix} \phi_{tur}(k+1) \\ \phi_{tur}(k) \\ \phi_{tur}(k-1) \\ u(k-1) \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ u(k) \\ I_m \end{bmatrix} v(k) + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} w(k),$$

$$y(k) = \begin{bmatrix} 0 & 0 & D & 0 & -DN \end{bmatrix} \begin{bmatrix} \phi_{tur}(k+1) \\ \phi_{tur}(k) \\ \phi_{tur}(k-1) \\ u(k-1) \\ u(k-2) \end{bmatrix} + w(k), \quad (7)$$

where $I_l \in \mathbb{R}^{l \times l}$ represent the identity matrix, with $l \in \mathbb{N}^*$. However, since the past command laws do not need to be estimated, we can reduce the estimation model to the form:

$$\begin{bmatrix} \phi_{tur}(k+2) \\ \phi_{tur}(k+1) \\ \phi_{tur}(k) \end{bmatrix} = \begin{bmatrix} A_{tur} & 0 & 0 \\ I_n & 0 & 0 \\ 0 & I_n & 0 \end{bmatrix} \begin{bmatrix} \phi_{tur}(k+1) \\ \phi_{tur}(k) \\ \phi_{tur}(k-1) \end{bmatrix} + \begin{bmatrix} r(k) \\ 0 \\ 0 \end{bmatrix} ,$$

$$y(k) = [0 \ 0 \ D] \begin{bmatrix} \phi_{tur}(k+1) \\ \phi_{tur}(k) \\ \phi_{tur}(k-1) \end{bmatrix} - DNu(k-2) + w(k). \quad (8)$$

### 3. LOW-COMPUTATIONAL COST ESTIMATION

This section contains three parts. First, the methodology of the filter synthesis with structure constraints is given. Then, the estimation of atmospheric turbulence is presented to fit the proposed methodology. Finally, the synthesis algorithm is presented.

#### 3.1 Filter synthesis

For the estimation problem, the related state-space standard form associated to the controller synthesis is (Zhou et al. (1996)):

$$\begin{cases} x(k+1) = Ax(k) + B_1 r(k) + e(k), \\ z(k) = x(k), \\ y(k) = C_2 x(k) + D_{21} r(k), \end{cases} \quad (9)$$

where $x \in \mathbb{R}^{n_x}$ is the state vector, $y \in \mathbb{R}^p$ is the measured output vector, $e \in \mathbb{R}^{n_x}$ is the control input vector and $r \in \mathbb{R}^{n_u}$ and $z \in \mathbb{R}^{n_z}$ are respectively the exogenous inputs and outputs. The Kalman filter results from the minimization of the $\mathcal{H}_2$ norm of the transfer function between $r$ and $z$, also noted $T_{r \rightarrow z}(L)$, where the matrix $L \in \mathbb{R}^{n_z \times p}$ corresponds to the filter gain. Without loss of generality for the Kalman problem, $r$ is considered as a zero-mean white gaussian noise with identity covariance matrix $I_{n_r}$. Then, the objective is to find a state feedback gain $L$ that defines the control law $e(k) = -Ly(k)$ that minimizes the cost function:

$$J(L) = ||T_{r \rightarrow z}(L)||_2^2. \quad (10)$$

The closed-loop state-space form can be rewritten as:

$$\begin{cases} x(k+1) = A x(k) + B(L) r(k), \\ z(k) = x(k), \end{cases} \quad (11)$$

where $A(L) = A - LC_2$ and $B(L) = B_1 - LD_{21}$. Therefore, the value of the criterion $J(L)$ is calculated as follows:

$$J(L) = \text{trace} [W_c(L)] = \text{trace} [B^T(L)W_o(L)B(L)], \quad (12)$$

where $W_c(L) > 0$ and $W_o(L) > 0$ are respectively the controllability and observability Gramians. They can be obtained by solving the following discrete-time Lyapunov equations (Anderson and Moore (1990)):

$$A^T(L)W_o(L)A(L) - W_o(L) + I_{n_z} = 0, \quad (13)$$

$$A(L)W_c(L)A^T(L) - W_c(L) + B(L)B^T(L) = 0. \quad (14)$$

To minimize the $\mathcal{H}_2$ norm, we use an algorithm based on the gradient of $J$ for a given matrix $L$, noted $\nabla J(L)$. As
shown in Apkarian et al. (2008) and Rautert and Sachs (1997), for the system described by equations (9), the gradient can be obtained from the following relations:

\[
\text{trace}[dW_c] = \text{trace}[\nabla J(L)^T dL] .
\] (15)

**Theorem 1.** Given a discrete-time system described by equations (9) and (11), the equation of the gradient of the cost function (12) is as follows:

\[
\nabla J(L) = -2W_o(L) \left( A(L)W_c(L)C_2 + B(L)D_{21}^T \right) .
\] (16)

**Proof.**

For the sake of clarity, the dependence on \( L \) of the matrices are dropped. Thus, we note \( \psi \) the Lyapunov equation of the controllability Gramian:

\[
\psi = AW_cA^T - W_c + BB^T .
\] (17)

By differentiating the variable \( \psi \) according to \( W_c \), one obtain:

\[
\psi dW_c = AdW_cA^T - dW_c
\] (18)

and differentiating with respect to \( L \), one obtain:

\[
\psi dL = -AW_cC_2^T dL^T - dLC_2W_cA^T - BD_{21}^T dL^T - dLD_{21}B^T .
\] (19)

As shown in (14), \( \psi = 0 \), then we have \( d\psi = 0 \). Therefore, we may write:

\[
\psi dW_c = -\psi dL
\] (20)

\[
AdW_cA^T - dW_c = AW_cC_2^T dL^T + dLC_2W_cA^T + BD_{21}^T dL^T + dLD_{21}B^T .
\] (21)

Using equation (13), the first term of equation (15) becomes:

\[
\text{trace}[dW_c] = \text{trace}[-A^T W_o AdW_c + W_o dW_c]
\] (22)

\[
= \text{trace}[-W_o (AdW_cA^T + dW_c)] .
\] (23)

The application of the equality (20) into (21) provides:

\[
\text{trace}[dW_c] = -\text{trace}[W_o Aw_o C_2^T dL^T + W_o dLC_2W_cA^T + W_o BD_{21}^T dL^T + W_o dLD_{21}B^T] .
\] (24)

\[
= -2\text{trace}[C_2W_cA^T + D_{21}B^T]W_o dL .
\] (25)

We finally obtain the equivalence between the last term in equation (15) and the expression given in equation (16):

\[
-2\text{trace}[C_2W_cA^T + D_{21}B^T]W_o dL = \text{trace}[\nabla J^T dL] .
\] (26)

3.2 Application AOS

The use of a low number of Zernike polynomials can be justified by the fact that the first spatial frequencies are those that have the high influence on the image phase. As stated before, most authors consider less than 15 Zernike polynomials model atmospheric turbulence effects on the image. Nevertheless, since the main objective is to compensate the aberrations caused by turbulence as well as possible, considering a large number of Zernike polynomials allows to get a better correction. With the arrival of the new generation of ground-based telescopes, this improvement will be possible with the very large mirror.

Thus, the aim of proposed method is to be able to synthesize a reduced-order filter gain using turbulence model with large number of Zernike modes. Since the algorithm does not synthesize a full-order gain, the computational cost is significantly reduced for the synthesis and the estimation.

Before providing the synthesis algorithm, the model for estimating the atmospheric turbulence (8) is presented according to the standard form (9), which allows to synthesize the reduced-order gain filter using the proposed method. The only manipulation is to take the noise inputs in the vector \( r(k) = [\hat{v}(k)^T \, \hat{w}(k)^T]^T \), where:

\[
\begin{cases}
\hat{v}(k) = B_1 \hat{v}(k), \\
\hat{w}(k) = D_{21} \hat{w}(k).
\end{cases}
\] (27)

Hence:

\[
\begin{bmatrix}
\phi_{\text{tur}}(k + 2) \\
\phi_{\text{tur}}(k + 1) \\
\phi_{\text{tur}}(k)
\end{bmatrix}
= \begin{bmatrix}
A_{\text{tur}} & 0 & 0 \\
I_n & 0 & 0 \\
0 & I_n & 0
\end{bmatrix}
\begin{bmatrix}
\phi_{\text{tur}}(k + 1) \\
\phi_{\text{tur}}(k) \\
\phi_{\text{tur}}(k - 1)
\end{bmatrix}
+ \begin{bmatrix}
B_1 \\
0 \\
0
\end{bmatrix}
\begin{bmatrix}
r(k) + e(k) \\
0 \\
0
\end{bmatrix}
\]

\[
\begin{bmatrix}
\phi_{\text{tur}}(k + 1) \\
\phi_{\text{tur}}(k) \\
\phi_{\text{tur}}(k - 1)
\end{bmatrix}
= \begin{bmatrix}
0 \\
0 \\
D_{21}
\end{bmatrix}
r(k)
\]

In order to find a Kalman filter that corresponds to \( H_2 \) norm where the transfer \( T_{r \rightarrow z} \) is minimized, we use the analogy between \( H_2 \) and linear quadratic Gaussian (LQG) synthesis problems given in Safonov et al. (1981). Thus, the matrices \( B_1 \) and \( D_{21} \) are determined as follow:

\[
\begin{bmatrix}
\Sigma_v \\
\Sigma_w
\end{bmatrix}
= \begin{bmatrix}
B_1 B_1^T \\
D_{21} D_{21}^T
\end{bmatrix}
\] (28)

where \( B_1 \) and \( D_{21} \) are obtained from a singular value decomposition of \( \Sigma_v \) and \( \Sigma_w \) respectively.

The objective of replacing the ARE with another method in the optimal filter synthesis is to be able to modify the structure of the filter gain \( L \) to our convenience. The advantage of this modification is used to synthesize a reduced-order filter gain. Thus, instead of synthesizing the
gain \( L \), we synthesize a reduced-order filter gain \( \hat{L} \), with \( L = F\hat{L} \) and the matrix \( F \) defined as follows:

\[
F = \begin{bmatrix} \hat{n} \\ 0 \end{bmatrix},
\]

(27)

with \( \hat{n} \ll n \) defines the order of the filter gain.

### 3.3 The Algorithm

In the following, we present the main elements of the algorithm. By "cycle" we mean the whole steps of actualization of the filter gain \( \hat{L} \) corresponding to one iteration of the main loop. \( \hat{L}_i \) represents the filter gain found at the \( i \)-th cycle. At each iteration, we evaluate \( J(\hat{L}_i) \) and \( \nabla J(\hat{L}_i) \). The initializing matrix \( \hat{L}_0 \) can be any matrix as long as it is proven to stabilize the system. The main loop is stopped if:

- the number of cycles exceeds the limit imposed by the user,
- the number of iterations for the secondary loop, defined below, hugely increases.

The secondary loop is indexed by \( j \), where \( \hat{L}_j \) represents the filter gain found at the \( j \)-th iteration. The secondary loop aims to evaluate the step of gradient descent and consists in the following steps:

1. The choice of \( \rho \) is chosen. For instance, we can set \( \rho = s^j \), with \( 0 < s < 1 \). The choice of \( s \) is also defined by the user and it has a great influence on the time needed for the calculations. A slow but precise decrease can be ensured by an \( s \) close to 1.

2. \( \hat{L}_j \) is computed according to

\[
\hat{L}_j = \hat{L}_i - \rho\nabla J(\hat{L}_i)
\]

3. The stability of the closed-loop system is analyzed. Since we work on discrete-time system, we search of the eigenvalues of \( A - \hat{L}_jC_\phi \), with \( \hat{L}_j = F\hat{L}_j \), have a magnitude smaller than 1. Thus, we are not concerned by all eigenvalues but only by the largest magnitude eigenvalue. Therefore, we can find a large number of fast and efficient algorithms to get the largest magnitude eigenvalue. If the filter is unstable, we increment \( j \) and restart from step (1) of the present loop.

4. The cost function decreasing is tested. If

\[
J(\hat{L}_i) - J(\hat{L}_j) > \epsilon
\]

we keep the gain \( \bar{L}_{i+1} = \hat{L}_j \) and begin the next cycle; otherwise, we increment \( j \) and restart from step (1) of the present loop. If \( j \) increases a lot, we end the program by exiting from the both loops and hence \( L = \hat{L}_i \).

**Remark.** Since the matrix \( A_{tur} \) has eigenvalues with a module smaller than 1 as stipulated in Petit (2006), we can initialize the filter gain \( \hat{L} \) with a zero-valued matrix.

### 4. SIMULATION RESULTS

For simulation purposes, the numerical values of \( A_{tur} \), \( D, N, \Sigma_u \) and \( \Sigma_w \) are those provided by L2TI and ONERA. \( D/T \) for the AO bank (Petit (2006)).

Since the dynamic model of the DM is neglected, the control law applied to it is \( u(k - 1) = -P\hat{\phi}_{tur}(k) \), where \( \hat{\phi}_{tur} \) is the estimation of atmospheric turbulence. Since \( \mathcal{H}_2 \) synthesis problem can be split into a Kalman filter synthesis and an LQR control, the matrix \( P \) can be easily found as a least-square solution \( P = (N^T N)^{-1}N^T \).

As stated earlier, turbulence is precisely described by an infinite number of Zernike modes, but the 10 first ones have a greater impact on the AOS. Consequently, the reduced model, on which a Kalman filter is synthesized, involves 30 modes (8), 149-modes turbulent model to simulate the aberrations introduced by atmospheric turbulence. For comparison purposes, we add results of a Kalman filter based on a 149-modes model. To show the efficiency of the proposed procedure, we take 30 modes for the reduced-order filter gain. Therefore, we can compare the performances of the proposed filter with the one obtained with the Kalman filter of the reduced model. Consequently, the ponderation filter \( F \) is composed of a 30-sized identity matrix (27). The performances of the closed-loop AOS is evaluated in terms of the sum of the variance of the residual phase (denoted as \( VAR \)), defined as follows:

\[
VAR(K) = \frac{1}{K} \sum_{k=0}^{K} \phi_{res}(k)^T \phi_{res}(k).
\]

Before comparing performances, we present the efficiency of proposed algorithm. In Fig. 4 and Fig. 5, we show how many cycles are needed to achieve the minimal cost function with models composed of 10 and 149 Zernike modes respectively. We can see that all step values make the cost function converge to its minimum value without a great difference in the number of cycles needed. Nevertheless, the execution time of one cycle is about 0.035 sec for 30 modes and 2.58 sec for 447 modes. These results are obtained using a Quad Core 2.67 GHz processor.

Fig. 6 compares the variance of the residual phases induced by both Kalman and the proposed filter. As it can be noticed, we obtain a significant improvement in performances using the proposed solution. Thus, our solution presents a compromise between the large-scale Kalman filter (149-Zernike modes) and the reduced one (10-Zernike modes).

### 5. CONCLUSION

Through this paper, a novel solution has been proposed for AOSs. Although the filter gain requires a priori more time to be calculated than the 30-modes Kalman filter, this can be done offline. On the other hand, with the proposed gradient algorithm, we can easily define the structure of the filter gain.

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Since it is impossible for a Kalman filter to reach optimality for AOSs due to the fact that turbulence is described by an infinite number of Zernike modes, we propose a solution to find a filter gain that approaches the optimal solution with low computational cost. As seen in simulations, the behavior of our filter is a good compromise that provides a better performance than a 30-modes Kalman filter and less computations cost than a 447-modes Kalman filter.

As forthcoming works, we project to add robust performances constraints in the filter synthesis with reduced-order gain.

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