Robust Detection of Biasing Attacks on Misappropriated Distributed Observers via Decentralized $H_\infty$ synthesis

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Abstract—We develop a decentralized $H_\infty$ synthesis approach to detection of biasing misappropriation attacks on distributed observers. Its starting point is to equip the observer with an attack model which is then used in the design of attack detectors. A two-step design procedure is proposed. First, an initial centralized setup is carried out which enables each node to compute the parameters of its attack detector online in a decentralized manner, without interacting with other nodes. Each such detector is designed using the $H_\infty$ approach. Next, the attack detectors are embedded into the network, which allows them to detect misappropriated nodes from innovation in the network interconnections.

I. INTRODUCTION

The need to protect control systems from malicious attacks has led to an emergence of methodologies for resilient control. Resilient control schemes intend to enhance tolerance of control systems to attacks. The interest in the resilience problem has increased substantially after situations were discovered where an adversary was able to compromise integrity of a control system by injecting a malicious input into the measurements, which was not detected by bad data detection units [2].

Cooperative networked control systems are particularly vulnerable to such attacks. For instance, in networks of observers [4] fidelity of information is crucial, it makes possible estimation of the plant even when it cannot be reliably estimated from local measurements. A misappropriated observer node can provide a false information to its neighbours, and use them to bias the entire network. On the other hand, as this paper shows, information sharing between network nodes provides opportunities for monitoring integrity of distributed filter networks.

This paper considers the problem of detection of malicious attacks, known as biasing attacks [10], on distributed state observers. The problem was posed originally in [3], it is motivated by the necessity to enhance resilience properties of a general class of distributed state estimation networks such as those introduced in [5], [7], [11], [14]. It is concerned with a situation where one of the observers in the network is misappropriated and is used to supply a biased information to its neighbours.

While we adopt the same bias injection attack model as in [3] and are concerned with detecting the same biasing behaviour of misappropriated nodes (also cf. [9]), our approach to the synthesis of attack detectors is different from [3]. It is based on the decoupling technique developed in [15]. This allows us to dispense with several difficulties of the vector dissipativity approach adopted in [3]. First and foremost, our approach provides the observer nodes with a better computational autonomy. In this paper, the process of computing the characteristics of an attack detector at each node is independent of other nodes. Although an initial centralized setup is required for this, it involves only characteristics of the communication network, and can be completed without knowledge of the system and the filter characteristics. This contrasts our results with the technique in [3] where the design conditions are coupled. As a by-product of decentralization, our technique applies to more general time-varying distributed filters. It also brings several other improvements, which simplify tuning the detector. At the same time, the proposed scheme retains advantages of the attack detection scheme developed in [3]. It is robust against uncertainties in the sensors and the plant model and relies on the same sensory and interconnection data as the networked observer it seeks to protect.

The paper begins with presenting a biasing attack model from [3] and also gives a background on the distributed filtering in Section II respectively. Section III presents the problem formulation and our main results, which allow one to construct a collaborative attack detector. The design technique is described in Section IV. The conclusions are given in Section V.

Notation: $\mathbb{R}^n$ denotes the real Euclidean $n$-dimensional vector space, with the norm $\|x\| = (x^T x)^{1/2}$; here the symbol $^T$ denotes the transpose of a matrix or a vector. The symbol $I$ denotes the identity matrix. For real symmetric $n \times n$ matrices $X$ and $Y$, $Y > X$ (respectively, $Y \geq X$) means the matrix $Y - X$ is positive definite (respectively, positive semidefinite). The notation $L_2[0, \infty)$ refers to the Lebesgue space of $\mathbb{R}^n$-valued vector-functions $z(t)$, defined on the time interval $[0, \infty)$, with the norm $\|z\|_2 = (\int_0^\infty \|z(t)\|^2 dt)^{1/2}$ and the inner product $\int_0^\infty z_1(t)z_2(t) dt$.

II. BIASING MISAPPROPRIATION ATTACKS ON DISTRIBUTED OBSERVERS

A distributed observer problem under consideration involves estimation of the state of a time varying plant

$$\dot{x} = A(t)x + B(t)w, \quad x(0) = x_0, \quad (1)$$

subject to an unknown modeling disturbance $w$, from a collection of measurements

$$y_i = C_i(t)x + D_i(t)u_i, \quad i = 1, 2, \ldots, N, \quad (2)$$

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taken at \(N\) nodes of a sensor network, and also affected by measurement disturbances \(v_i\). The distributed estimation problem requires that the measurements are to be processed at the sensor nodes, rather than centrally. For this, sensors-observers are interconnected into a network, so that the constituent nodes can share their pre-processed data and can enhance their local estimates of the plant state.

To describe the problem mathematically, let us assume that the state \(x\) and the disturbance \(w\) are respectively in \(\mathbb{R}^n, \mathbb{R}^m\), and each measurement \(y_i\) is in \(\mathbb{R}^{p_i}\). The disturbances \(w\) and \(v_i \in \mathbb{R}^{m_i}\) will be assumed \(L_2\) integrable on \([0, \infty)\). The initial state \(x_0\) is also unknown. A typical distributed estimation problem involves constructing a network of filters of the form

\[
\dot{x}_i = A(t)x_i + L_i(t)(y_i - C_i(t)x_i) + \sum_{j \in \mathbb{N}_i} K_{ij}(t)(c_{ij} - W_{ij}\dot{x}_i), \quad \dot{x}_i(0) = \xi_i, \quad (3)
\]

each generating an estimate \(\hat{x}_i(t)\) of the plant state \(x(t)\) using its measurement \(y_i\) and the information received from the neighbours, in the form of a \(p_i\)-dimensional signal

\[
c_{ij} = W_{ij}\dot{x}_j + H_{ij}v_{ij}, \quad j \in \mathbb{N}_i;
\]

here \(\mathbb{N}_i\) denotes the neighbourhood of agent \(i\), i.e., the set of network nodes that communicate their information to \(i\). Since the plant is time-varying, the filter coefficients \(L_i, K_{ij}\) are allowed to be time-varying as well.

The matrices \(W_{ij}\) determine which part of the vector \(\dot{x}_j\) is made available to node \(i\) by node \(j\). Typically, distributed observers are required where the plant may not be detectable from local measurements at some of the nodes, and the signals \(c_{ij}\) serve to complement the local measurements with an additional information. Mathematically, to obtain an unbiased estimate of \(x\), node \(i\) may require a portion of \(\dot{x}_j\) which lies in the subspace of states undetectable from \(y_i\). The matrix \(W_{ij}\) can be thought of as ‘projecting’ \(\dot{x}_j\) onto that subspace. However, the communication channels which deliver this information are typically subject to disturbances; this is reflected in the term \(H_{ij}v_{ij}\) in (4).

The problem is to determine estimator gains \(L_i\) and \(K_{ij}\) in (3) to ensure that each estimate \(\hat{x}_i\) (or a part of it) converges to \(x(t)\) in some sense, and that some filtering performance against disturbances is guaranteed. On the other hand, an adversary may seek to prevent this from happening. A common means for interfering with a normal operation of the system involve injecting false data into the measurements or communications [6], however consideration is also given to misappropriation attacks where adversary gains control over the control algorithm and modifies it according to its strategic goals [8]. In line with this idea, in [3] we considered a situation where the attacker interferes with dynamics of the hijacked node by injecting a biasing input into the filter. In this paper we extend this model to consider a similar type of attack on the network of time-varying observers. Specifically, we consider the situation where the adversary substitutes one or several observers (4) with

\[
\dot{x}_i = A(t)x_i + L_i(t)(y_i - C_i(t)x_i) + \sum_{j \in \mathbb{N}_i} K_{ij}(t)(c_{ij} - W_{ij}\dot{x}_i) + F_if_i, \quad \hat{x}_i(0) = \xi_i. \quad (5)
\]

Here \(F_i \in \mathbb{R}^{n_i \times n_{fi}}\) is a constant matrix and \(f_i \in \mathbb{R}^{n_{fi}}\) is the unknown signal representing an attack input. In the following, we will present an algorithm for detecting and tracking these unknown inputs.

Following [3], we will consider a class of attacks on the filter (5) consisting of biasing inputs \(f_i(t)\) of the form

\[
f_i(t) = f_{i1}(t) + f_{i2}(t), \quad (6)
\]

where the Laplace transform of \(f_{i1}(t), f_{i1}(s)\), is such that \(\sup_\omega |\omega f_{i1}(j\omega)|^2 < \infty\) and \(f_{i2} \in L_2[0, \infty)\). It can be shown that one can select a proper \(n_{fi} \times n_{fi}\) transfer function \(G_i(s)\) for which the system in Fig. 1 is stable and has the property

\[
\int_0^\infty \|f_i - \hat{f}_i\|^2 dt < \infty, \quad (7)
\]

which holds for all inputs that admit decomposition (8). In particular, bias injection attack inputs of the form ‘constant + an exponentially decaying transient’ generated by a low pass filter introduced in [10] have the form (8), and therefore can be ‘tracked’ using a system shown in Fig. 1. Of course, in reality it is not possible to track covert attack inputs. However, the model in Fig. 1 is useful in that it allows us to associate with the class of biasing attack inputs a system

\[
\dot{e}_i = \Omega e_i + \Gamma_1 \nu_i, \quad e_i(0) = 0, \quad (8)
\]

\[
f_i = \Upsilon e_i,
\]

where \(\nu_i = \hat{f}_i - f_i\) is an \(L_2\)-integrable input, according to (7).

In practice, the transfer function \(G_i(s)\) must be selected by the designer according to an anticipated behaviour of the attack inputs \(f_i(t)\). For example, for the mentioned class of bias injection attacks of the form ‘constant + an exponentially decaying transient’, one can choose \(G_i(s)\) to be a first order low pass filter, \(G_i(s) = \frac{g_i}{1 + \beta_3 s}\). The corresponding coefficients of the system (8) then take the form

\[
\Omega = \begin{bmatrix} 0 & I \\ 0 & -2\beta_3 I \end{bmatrix}, \quad \Gamma_1 = \begin{bmatrix} 0 \\ \Gamma_1 \end{bmatrix}, \quad \Upsilon = [I \ 0]. \quad (9)
\]

The choice of the transfer functions \(G_i(s)\) and the corresponding system (8) will affect performance of the attack detectors to be introduced later in the paper. For instance, in the above example, selecting \(\beta_3, g_i\) enables tuning the performance of the attack detectors.
III. Problem Formulation

First, let us summarize the information which the observer nodes can utilize to detect an attack. Each node has two innovation signals available,

\[ \zeta_i = y_i - C_i(t)\hat{x}_i = C_i(t)(x - \hat{x}_i) + D_i(t)v_i, \]

(10)

\[ \zeta_{ij} = c_{ij} - W_{ij}\hat{x}_i, \]

(11)

The innovation \( \zeta_i \) symbolizes the new information contained in the measurement acquired by node \( i \), compared with its own prediction of that information. Likewise, the innovation \( \zeta_{ij} \) symbolizes the new information contained in the message that node \( i \) receives from its neighbour \( j \in N_i \). Similar to [3], these innovations will play an instrumental role in detecting a rogue behaviour of misappropriated nodes. Both signals are readily available at node \( i \); computing them only requires the local measurement \( y_i \) and the neighbour messages \( c_{ij}, j \in N_i \), available at node \( i \), along with \( \hat{x}_i \); see [5].

The problem of detecting a biasing attack of the form (6) on the observer network comprised of observers [5] consists in designing a network of attack detectors

\[ \mu_i = \alpha_d(t)\mu_i + L_d,i(t)(\zeta_i - W_{di}\mu_i) + \sum_{j \in N_i} K_{d,ij}(t)(\zeta_{ij} - W_{d,ij}(\mu_j - \mu_i)), \]

(12)

\[ \varphi_i = C_{d,i}\mu_i, \quad \mu_i(0) = \mu_{i,0}, \]

which guarantee that

\[ \int_0^{+\infty} \|\varphi_i - f_i\|^2 dt < +\infty. \]

(13)

Here, \( \alpha_d(t), L_d,i(t), K_{d,ij}(t), W_{d,i}, W_{d,ij}, C_{d,i} \) are matrix valued coefficients to be found.

According to (13), the output of each detector subsystem (12) is required to track \( f_i \) in the \( L_2 \) sense. This makes these outputs suitable as indicators of the biasing attack. Note that each detector relies on the information received from its neighbouring nodes contained in the innovation signals \( \zeta_{ij} \).

IV. Design of Attack Detectors

Define the estimation error at node \( i, e_i = x - \hat{x}_i \). It follows from (11) that the dynamics of this error are described by

\[ \dot{e}_i = (A(t) - L_i(t)C_i(t) - \sum_{j \in N_i} K_{ij}(t)W_{ij})e_i + \sum_{j \in N_i} K_{ij}(t)W_{ij}e_j + B(t)w - L_i(t)D_i(t)v_i - \sum_{j \in N_i} K_{ij}(t)H_{ij}v_{ij} - F_i f_i, \quad e_i(0) = x_0 - \xi_i, \]

(14)

Using the representation of the attack input \( f_i = \Upsilon_i e_i - \nu_i \) and (8), the input \( f_i \) can be eliminated from (14). This will result in the following extended system:

\[ \dot{e}_i = (A(t) - L_i(t)C_i(t) - \sum_{j \in N_i} K_{ij}(t)W_{ij})e_i + \sum_{j \in N_i} K_{ij}(t)W_{ij}e_j + B(t)w - L_i(t)D_i(t)v_i - \sum_{j \in N_i} K_{ij}(t)H_{ij}v_{ij} - F_i f_i, \quad e_i(0) = x_0 - \xi_i, \]

(15)

Also, using (10), (11), define outputs of the extended system (15) as

\[ \zeta_i = C_i(t)e_i + D_i v_i, \]

(16)

\[ \zeta_{ij} = -W_{ij}(e_i - e_j) + H_{ij}v_{ij}, \quad j \in N_i. \]

(17)

These outputs are available at each node of the network and will be used as inputs to an attack detector, whose function is to estimate the state of the system (15) and generate an output \( \varphi_i \) that converges to \( f_i \) and \( f_i \) while attenuating the disturbances.

The observer which we propose below for estimating the combined state \( (e_i, e_j) \) of this system is a time-varying version of the observer introduced in [3]. This observer is as follows:

\[ \dot{\hat{e}}_i = (A(t) - L_i(t)C_i(t) - \sum_{j \in N_i} K_{ij}(t)W_{ij})\hat{e}_i + \sum_{j \in N_i} K_{ij}(t)W_{ij}\hat{e}_j - F_i \Upsilon_i \hat{e}_i + L_i(\zeta_i - C_i e_i) + \sum_{j \in N_i} K_{ij}(t)(\zeta_{ij} - W_{ij}(\hat{e}_i - \hat{e}_j)), \]

\[ \dot{\hat{e}}_j = \Omega_i \hat{e}_i + \hat{L}_i(\zeta_i - C_i e_i) + \sum_{j \in N_i} K_{ij}(t)(\zeta_{ij} - W_{ij}(\hat{e}_i - \hat{e}_j)) + \Upsilon_i \hat{e}_j, \]

\[ \varphi_i = \Upsilon_i \hat{e}_i, \quad \hat{e}_i(0) = 0, \quad \hat{e}_j(0) = 0. \]

(18)

From now on, our effort is directed towards finding a constructive method for computing the coefficients of this observer. We seek to obtain the gains \( L_i(t), K_{ij}(t), L_i(t), K_{ij}(t) \) such that the output \( \varphi_i \) of each filter (18) converges to \( f_i \). This will establish the filters (18) as biasing attack detectors. The inputs to the observer (18) are innovation signals (10), (11).

Despite the similarity between the filter (18) and the filter introduced in [3] for the similar task, the time-varying nature of the problem under consideration requires us to revisit the design method obtained in [3]. The design conditions proposed in [3] involve solving certain coupled linear matrix inequalities. Although similar inequalities can be derived for the problem considered here, they will involve derivatives of the vector storage functions and will therefore be differential matrix inequalities, with time-varying coefficients. Such inequalities are very difficult to solve, even using centralized solver facilities. For this reason, here we develop an alternative technique for computing the coefficients of the observer (18). Although our task of selecting the gains \( L_i, K_{ij}, L_i, K_{ij} \) so that the observer (18) attenuates the
\[ \mathcal{L}_2 \)-integrable disturbances \( w, v_1, v_{ij}, v_t \), while guaranteeing \( \mathcal{L}_2 \) convergence and an \( H_{\infty} \) performance of the distributed attack detector, remains unchanged we propose a different technique which suits time-varying problems such as the one considered here. The idea of this technique is to decentralize the design process (but not the detectors themselves) to make it tractable.

To explain the decentralized design of the attack detector, let \( z_i = e_i - \hat{e}_i \), \( \delta_i = e_i - \hat{e}_i \) be estimation errors of the observer (18). It is easy to see from (18) that these errors evolve according to the equations

\[
\dot{z}_i = (A(t) - \bar{L}_i(t)C_i(t))z_i - \sum_{j \in \mathbb{N}_i} \bar{K}_{ij}^i(t)W_{ij}z_j - F_i Y_i \delta_i
\]

\[
- \sum_{j \in \mathbb{N}_i} \bar{K}_{ij}^i(t)(W_{ij}z_j + H_{ij}v_{ij}) + Bw
\]

\[
- L_i(t)D_i(t)v_i + F_i v_i,
\]

\[
\tilde{\delta}_i = \Omega i \delta_i - \bar{L}_i(t)C_i(t)z_i - \sum_{j \in \mathbb{N}_i} \bar{K}_{ij}^i(t)W_{ij}z_j + \Gamma_i v_i
\]

\[
- \sum_{j \in \mathbb{N}_i} \bar{K}_{ij}^i(t)(W_{ij}z_j + H_{ij}v_{ij})
\]

(19)

Here we used the notation \( \bar{L}_i = L_i + \bar{L}_i, \bar{K}_i = K_i + \bar{K}_i \). Also, let us introduce signals

\[
\eta_{ij} = W_{ij}z_j, \quad j \in \mathbb{N}_i.
\]

(20)

Altogether, for each node \( i \), \( q_i \) such signals are introduced, where \( q_i \) is the cardinality of the set \( \mathbb{N}_i \), also known as in-degree of node \( i \). Each signal \( \eta_{ij} \) is of dimension \( p_{ij} \), i.e., it matches the dimension of the corresponding communication signal \( e_{ij} \). The signals \( \eta_{ij} \) serve as interconnection signals for the large-scale system (19). Then the error system (19) can be written as

\[
\frac{d}{dt} \lambda_i = (A_i(t) - L_i(t)C_i(t))\lambda_i + B(t) \begin{bmatrix} v_i \\ \delta_i \end{bmatrix}
\]

\[
-L_i(t)D_i(t)v_i,
\]

where we used the following notation:

\[
\lambda_i = \begin{bmatrix} z_i \\ \delta_i \end{bmatrix}, \quad \bar{\delta}_i = \begin{bmatrix} \delta_{i1} \cdots \delta_{iN} \end{bmatrix}^T,
\]

\[
\tilde{\eta}_i = \begin{bmatrix} (Z_{ij}^{-1/2}\eta_{ij})' \cdots (Z_{ij}^{-1/2}\eta_{ij})' \end{bmatrix}^T,
\]

\[
A_i(t) = A(t) - F_i Y_i, \quad B_i = \begin{bmatrix} B(t) F_i \\ 0 \end{bmatrix},
\]

\[
C_i(t) = \begin{bmatrix} C_i(t) & 0 \\ W_{ij} & 0 \end{bmatrix}, \quad L_i = \begin{bmatrix} \bar{L}_i & \bar{K}_{ij} & \cdots & \bar{K}_{ij} \\ L_i & \bar{K}_{ij} & \cdots & \bar{K}_{ij} \end{bmatrix}
\]

(21)

Here \( Z_{ij} i = 1, \ldots, N, j \in \mathbb{N}_i \) are certain square \( p_{ij} \times p_{ij} \) positive definite matrices. It will be assumed that each matrix \( E_{ij}(t) = D_i(t)D_i(t)^T \) is positive definite for all \( t \).

The system (21) can be regarded as an uncertain system affected by the disturbances \( w, v_1, v_{ij} \) and signals \( \eta_{ij}, Z_{ij}^{-1/2}\eta_{ij} \). The latter signals will be treated as fictitious disturbances. This allows us to apply the \( H_{\infty} \) filtering theory to obtain a gain coefficient \( \lambda_i(t) \) which guarantees that the impact of the disturbances on the errors \( z_i, \delta_i \) is attenuated.

Introduce collection of positive definite \((n + n_f) \times (n + n_f)\) block-diagonal matrices \( R_i, X_i, i = 1, \ldots, N \), partitioned as

\[
R_i = \begin{bmatrix} R_i & 0 \\ 0 & \bar{R}_i \end{bmatrix}, \quad X_i = \begin{bmatrix} X_i & 0 \\ 0 & \bar{X}_i \end{bmatrix},
\]

with \( n \times n \) matrices \( R_i, X_i \) and \( n_f \times n_f \) matrices \( \bar{R}_i, \bar{X}_i \).

In addition, define the matrix

\[
\Phi = [\Phi_{ij}]_{i,j=1}^N
\]

(23)

composed of the blocks

\[
\Phi_{ij} = \begin{cases} \Delta_{ij}, & i = j, \\ -W_{ij}U_{ij}^{-1}W_{ij}, & i \neq j, j \in \mathbb{N}_i, \\ 0, & i \neq j, j \in \mathbb{N}_i, \end{cases}
\]

where

\[
U_{ij} = H_{ij}H_{ij}^T + Z_{ij}, \quad \Delta_i = \sum_{j \in \mathbb{N}_i} W_{ij}U_{ij}^{-1}Z_{ij}U_{ij}^{-1}W_{ij}.
\]

Also, let

\[
R = \text{diag}[R_1, \ldots, R_N], \quad \Delta = \text{diag}[\Delta_1, \ldots, \Delta_N].
\]

(i) the following linear matrix inequalities are satisfied

\[
R + \gamma^2(\Phi + \Phi' - \Delta) > I, \quad \bar{R}_i > I; \quad (24)
\]

\[
(25)
\]

(ii) each differential Riccati equation

\[
\dot{Y}_i = A_i Y_i + Y_i A_i^T - Y_i (C_i E_i^{-1} C_i - \frac{1}{\gamma^2} R_i) Y_i + B_i B_i^T; \quad (26)
\]

\[
Y_i(0) = X_i^{-1},
\]

has a positive definite symmetric bounded solution \( Y_i(t) \) on the interval \([0, \infty)\), i.e., for all \( t \geq 0, \alpha_1 I < Y_i(t) < \alpha_2 I \), for some \( \alpha_{1,2} > 0 \).
The network of observers\(^{(13)}\) with the coefficients \(L_i\), \(K_{ij}\), \(\hat{K}_i\), \(\hat{L}_i\), \(\hat{K}_{ij}\), obtained by partitioning the matrices
\[
L_i(t) = Y_i(t)C_i(t)E_i^{-1}(t).
\] (27)
according to\(^{(23)}\), guarantees that the noise- and attack-free system\(^{(15)}\) is exponentially stable, while in the presence of disturbances or an attack it holds that
\[
\int_0^{+\infty} \|\hat{x}_i(t) - L_i(t)z_i\|^2 dt < \infty \quad \forall i.
\]
The proof of the theorem is removed for brevity.

**Remark 1:** It follows from Theorem\(^{(1)}\) that \(z_i \in L_2[0, \infty)\), therefore every signal \(\eta_{ij}\) defined in\(^{(20)}\) is \(L_2\)-integrable. This allows us to conclude that every observer\(^{(21)}\) has a local disturbance attenuation property. Specifically, according to the \(H_\infty\) filtering theory\(^{(1)}\) it follows from the condition (ii) of Theorem\(^{(1)}\) that
\[
\int_0^T (z_i^2 \tilde{R}_i z_i + \delta_i^2 \hat{R}_i \delta_i) dt
\leq \gamma^2 \left( \|x_0 - \xi_i\|^2 + \int_0^T \|w\|^2 + \|v_i\|^2 \right.
\left. + \sum_{j \in N_i} \left( \|v_{ij}\|^2 + \|W_{ij} z_j \|^2 \right) dt \right)
\] (28)
This condition reveals the role of the matrices \(\tilde{R}_i\), \(\hat{R}_i\), and \(Z_{ij}\) included in the Riccati equation\(^{(25)}\) as design parameters. These matrices weigh the output error of the observer\(^{(19)}\) at node \(i\) against the information about the errors at the neighbouring nodes which supply information to node \(i\).

**V. CONCLUSION**

The paper has proposed a decentralized \(H_\infty\) synthesis method for the design of distributed observers for detecting biasing attacks on distributed filter networks. The proposed detectors can pick a biasing attack from local sensory information complemented with information extracted from the routine information exchange within the network. Our method accounts for the fact that such filters operate in noisy environments, therefore \(H_\infty\) performance of the proposed detectors against disturbances is also guaranteed.

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