A Distributed Approach for the Detection of Covert Attacks in
Interconnected Systems with Stochastic Uncertainties

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Abstract—The design of a distributed architecture for the
detection of covert attacks in interconnected Cyber-Physical
Systems is addressed in this paper, in the presence of stochastic
uncertainties. By exploiting communication between neighbors,
the proposed scheme allows for the detection of covert attacks
that are locally stealthy. The proposed methodology adopts
a decentralized filter, jointly estimating the local state and
the aggregate effect of the physical interconnections, and
uses the communicated estimates to obtain an attack-sensitive
residual. We derive some theoretical detection properties for
the proposed architecture, and present numerical simulations.

I. INTRODUCTION

Cyber-Physical Systems (CPSs) describe a class of large-
scale systems, where the physical components are integrated
with cyber resources, such as communication, control, and
monitoring infrastructures. They are an ever more common
class of systems, following the increased penetration of
information technology (IT) for monitoring and coordination
purposes in industrial plants and infrastructure systems.

Among the systems that can be described as CPSs, many
are safety critical, as their inadequate provision of service
may have severe consequences. This has led to a growing
interest in the literature on the subject of secure control, as
demonstrated by the recent special issue [1], as well as the
surveys [2], [3], and the works cited therein.

Several works in the literature rely on centralized archi-
tectures for monitoring CPS [4], [5], [6]. Implementation
of these architectures presents some disadvantages, however,
as it may require excessive computational power and com-
munication resources. Hence, distributed methods for attack
detection have been developed, of which [7], [8], [9], [10],
[11] are notable examples. These often draw upon the work
done in the Fault Detection and Isolation (FDI) literature (see
for instance [12], [13], [14]).

It has been shown in [4], [10], [15] that malicious agents can covertly misappropriate control systems by
carefully designing the signals they inject in the available
communication channels. In [10], the authors leveraged the
physical interconnections between subsystems to the de-
fender’s advantage. Specifically, an architecture based on
the combination of two observers permits to reveal misbehavior
in neighboring subsystems that is instead concealed in the
attacked one. In this paper, the problem is formulated in a
similar way, however, here we consider:

- A discrete-time linear stochastic model for each subsys-
tem instead of a continuous-time one.
- The proposed distributed detection architecture is based
on different estimation models: a minimum-variance
unbiased estimator jointly estimates the local states and
the aggregate effect of the neighbors’ interconnection.
- A detection method based on the statistical analysis of
a properly designed residual signal is proposed, and its
detectability properties are studied.

The distributed detection of attacks in stochastic systems
is also considered in [8]. However, the authors do not focus
on covert attacks, and do not build a distributed estimation
architecture to achieve this, but rather perform hypothesis
testing on appropriately processed output measurements.

The problem of unknown-input decoupling in the esti-
mation of stochastic systems has drawn great attention in
the past, and milestone contributions in the area include
[16]. A more general problem is solved in [17], where
unknown inputs also affect the measurement channel, while
[18] improves on previous results by designing a two-step
filter that also optimally estimates the input.

In this work, we adopt the filter presented in [18] to com-
pute a distributed estimate of the local state, by decoupling
it from the effect of the subsystem’s neighbors.

The rest of the paper is structured as follows: in Section II,
we formulate the considered problem. In Section III, the
decoupled distributed filter is presented, and the properties
of the state and unknown-input estimates are analyzed in
Sections IV and V. Following this, a novel detection strategy
is proposed in Section VI, where a suitable statistical test
is defined, and some of its properties are provided. Finally,
some numerical simulations are presented in Section VII.

Notation: For a vector $v \in \mathbb{R}^n$, $v[i]$ denotes its $i$-th
component. The identity matrix of dimension $n$ will be
defined as $I_n$, and $0_{n \times m} \in \mathbb{R}^{n \times m}$ is used to define a matrix
of all zeros; when clear from the context, the indices will
be omitted. We use notation $\text{col}_{j \in J} [x_j]$ and $\text{row}_{j \in J} [x_j]$
for the column or row concatenation of vectors $x_j, j$
belonging to a set of indices $J \subset \mathbb{N}$. The same notation is
Fig. 1: The network of interconnected subsystems and the internal structure of subsystem $S_i$ (under attack), equipped with a controller $C_i$ and a diagnoser $D_i$.

also used with matrices. Additionally, $\text{diag}_{j \in \mathcal{J}}[M_j]$ denotes block diagonal concatenation of matrices $M_j$, $j \in \mathcal{J}$. Given a random variable $x(k)$, $\mathbb{E}[x(k)]$ denotes its expected value. Furthermore, $\text{Cov}(x, y)$ denotes the covariance matrix of two random variables $x$ and $y$, and $\text{Var}(x) = \text{Cov}(x, x)$ is the covariance matrix of a random variable $x$.

II. PROBLEM FORMULATION

A. Model of CPS

Consider a CPS composed of $N$ subsystems $S_i$, which are interconnected through both physical and communication links. We consider the topology of the graphs defined by these links to be the same, i.e. a communication link between two subsystems is present if there is also a physical link. We define the set of neighbors of $S_i$ as $\mathcal{N}_i = \{j \in \{1 \ldots N\} | x_{ij} \neq 0\}$. The dynamics of $S_i$ is:

$$x_i(k+1) = A_i x_i(k) + B_i u_i(k) + \sum_{j \in \mathcal{N}_i} A_{ij} x_j(k) + w_i(k)$$

$$y_i(k) = C_i x_i(k) + v_i(k),$$

where $x_i \in \mathbb{R}^{n_i}$ is the state, $u_i \in \mathbb{R}^{m_i}$ is the control input, $y_i \in \mathbb{R}^{p_i}$ is the output measurement; $w_i \sim \mathcal{N}(0, W_i)$ and $v_i \sim \mathcal{N}(0, V_i)$ are process and measurement i.i.d. Gaussian noise, with known variance matrices $W_i \succeq 0$ and $V_i > 0$. Furthermore, we assume the initial condition $x_i(0) \sim \mathcal{N}(\bar{x}_i, \Pi_i)$, with $\Pi_i > 0$ and $\bar{x}_i$ known, and independent from $w_i(k)$ and $v_i(k)$ for all $k$. Matrices $A_i$, $A_{ij}$, $B_i$, and $C_i$ are supposed to be known by the local diagnoser. As shown in the schematic diagram in Figure 1, each subsystem is locally equipped with a controller $C_i$ and a diagnoser $D_i$, the latter of which exchanges information with their neighbors.

B. Attack model

From time $k = k_a$, we consider a covert attack on subsystem $S_i$. The attack is modeled as (see [4]):

$$x_i^a(k+1) = A_i^a x_i^a(k) + B_i^a \eta_i(k)$$

$$\gamma_i(k) = C_i^a x_i^a(k),$$

where $\eta_i$ is the attacker’s control input. We stress that $\eta_i$ is unknown to $D_i$; furthermore, it is arbitrarily defined by the attacker to steer $x_i$ away from its desired nominal trajectory. The signals $\eta_i$ and $\gamma_i$ are injected in the control and measurement channels, respectively, as follows:

$$\tilde{y}_i = y_i - \gamma_i$$

$$\tilde{u}_i = u_i + \eta_i,$$

where $u_i$ is the input as computed by the controller $C_i$. By mimicking the dynamics of $S_i$ in (2), the attacker can compensate the effects of $\eta_i$ through $\gamma_i$, thus making their action undetectable from the sole measurements observation.

Assumption 1: The attacker has perfect knowledge of the subsystem model, i.e. $(A_i^a, B_i^a, C_i^a) = (A_i, B_i, C_i)$. $	riangle$

The result of this attack is that the dynamics $x_i^a$ is superimposed to that of $S_i$. In the following result – a discretized version of Proposition 1 in [10] – the state of $S_i$ is decomposed in a healthy and an attacked component.

Proposition 1: Consider attack strategy (2), and let Assumption 1 hold. If the attacker’s initial state is $x_i^a(k_a) = 0$, the output received by the diagnoser unit $D_i$ is:

$$\tilde{y}_i(k) = y_i^h(k) = C_i x_i^h(k) + v_i(k) , \quad \forall k \geq k_a.$$

where $y_i^h$ is the output of the subsystem as if it were not affected by the attack.

Proof: Throughout this work, for reasons of space, proofs will be omitted. $lacksquare$

Remark 1: Proposition 1 provides a sufficient condition for stealthiness of the covert attack, and implies that, whatever the local estimate of the state, the residual error based on local measurements is not affected by the attack, as has been shown in the literature [4], [10]. $	riangle$

In this paper, we address the following:

Problem 1: Given a subsystem $S_i$ with dynamics as in (1) and an attack as in (2) from time $k_a$, and let Assumption 1 hold. Design a diagnoser $D_i$ to detect the attack. $	riangle$

III. DISTRIBUTED DETECTION FILTERS

Each local diagnosis unit $D_i$ is equipped with a decentralized estimator, based on the filter proposed in [18] in the context of centralized estimation. Each diagnosis unit $D_i$ then exchanges information with $D_j$, $j \in \mathcal{N}_i$, in order to compute the detection residual introduced in Section V. The state estimator is unbiased and guarantees minimum variance of the estimation error regardless of the presence of an unknown input [18].

We design the diagnostic unit $D_i$ such that the computed local estimates are decoupled from the neighbors of $S_i$. To achieve this, the interconnection terms can be treated as unknown inputs, and rewritten as:

$$\sum_{j \in \mathcal{N}_i} A_{ij} x_j = \text{row}_{j \in \mathcal{N}_i} [A_{ij}] \text{col}_{j \in \mathcal{N}_i} [x_j]$$

$$= E_i \xi_i = G_i \bar{E}_i \xi_i = G_i \xi_i,$$

where $\xi_i$ is the output of the subsystem as if it were not affected by the attack.
where \( G_i \) has full column rank, \( \tilde{E}_i \) is a matrix of weights and defines a vector of unknown inputs \( \xi_i \in \mathbb{R}^{g_i} \), which can be interpreted as the aggregate effect of all neighbors’ physical interconnection on dynamics (1). The following further assumptions are needed for all subsystems \( S_i \):

Assumption 2: Matrices \( C_i \) are such that \( \text{rank}(C_iG_i) = \text{rank}(G_i) = g_i \).

Assumption 3: The pair \((A_i, C_i)\) is observable.

Given the structure of (1), the filter design in [18] can be exploited to obtain unbiased minimum-variance local state and disturbance estimates \( \hat{x}_i \) and \( \hat{\xi}_i \), respectively. We obtain the following estimates of the local state and of the aggregate interconnections (note the presence of \( \hat{y}_i \) and the use of \( u_i \)):

\[
\hat{x}_i(k) = \tilde{A}_i(k)[A_i\hat{x}_i(k-1) + B_iu_i(k-1)] + \tilde{L}_i(k)\hat{y}_i(k)
\]

\[
\hat{\xi}_i(k-1|k) = M_i(k)[\hat{y}_i(k) + -C_i(A_i\hat{x}_i(k-1) + B_iu_i(k-1))]
\]

where

\[
\tilde{A}_i(k) \doteq (I - K_i(k)C_i)(I - G_iM_i(k)C_i)
\]

\[
\tilde{L}_i(k) \doteq K_i(k) + (I - K_i(k)C_i)G_iM_i(k).
\]

Note that these two matrices are related to each other as:

\[
\tilde{A}_i(k) = I - \tilde{L}_i(k)C_i.
\]

Remark 2: Note that (5b) depends on delayed information, as the estimate \( \hat{\xi}_i(k-1|k) \) is only available at time \( k \), once measurement \( \hat{y}_i(k) \) is available. This is to be expected, since the \( \xi_i \) dynamically affects the state, i.e. the effects of \( \hat{\xi}_i(k-1) \) can only be seen from \( \hat{y}_i(k) \).

We now repeat Theorem 12 in [18], which gives the theoretical properties of the estimates (5b) and (5a):

**Lemma 1 ([18, Thm.12]):** Consider the joint input and state estimator in (5), where \( M_i(k) \) satisfies:

\[
M_i(k)C_iG_i = I_{g_i}, \quad \forall k \geq 0.
\]

If \( M_i(k) \) and \( K_i(k) \) are designed as in [18], (5b) and (5a) are unbiased estimates of \( \xi_i(k-1) \) and \( x_i(k) \), minimizing the mean square error over the class of all linear unbiased estimates based on \( \hat{x}_i^k \) and \( y_i(k), 0 \leq k \leq k \).

**Remark 3:** Assumption 2 is a sufficient condition for the existence of an estimate which is decoupled from an unknown input \( \xi_i \), both in the stochastic [16] and in the deterministic case [19]. On the other hand, the decomposition \( G_i\tilde{E}_i \) is needed for the input estimation, as at most rank \((\tilde{E}_i)\) components can be estimated. By means of the decomposition in (4), \( \xi_i \) aggregates the independent components of the interconnection that influence \( x_i \).

In the following, we analyze the specific properties of both the state and unknown-input estimates \( \hat{x}_i \) and \( \hat{\xi}_i \).

IV. LOCAL STATE ESTIMATION

Let us start by considering the system in healthy conditions, by analyzing the estimation and residual errors under healthy mode of behavior:

\[
\epsilon_i^h(k|k) = x_i^h(k) - \hat{x}_i(k|k)
\]

\[
r_i(k|k) = \hat{y}_i(k) - C_i\hat{x}_i(k|k),
\]

where the superscript \( h \) has been added to highlight that the estimation error is considered in nominal conditions. We then analyze the estimation error under attack.

**Remark 4:** Note that, since \( \hat{y}_i = y_i^p \), from Proposition 1, the estimates in (5) only use information from the state which is not affected by the attack. As such, it is unnecessary to include the superscript \( h \) when analyzing \( \hat{x}_i \), as well as dealing with \( r_i \). Conversely, distinguishing between healthy and attacked information is crucial for error analysis.

Hence, the estimation error dynamics can be derived as:

\[
\epsilon_i^h(k) = \tilde{A}_i(k)\left[A_i\epsilon_i^h(k-1) + G_i\xi_i(k-1) + w_i(k-1)\right] - \tilde{L}_i(k)v_i(k)
\]

\[
= \tilde{A}_i(k)\left[A_i\epsilon_i^h(k-1) + w_i(k-1)\right] - \tilde{L}_i(k)v_i(k)
\]

where the interconnection term \( G_i\xi_i(k-1) \) is removed thanks to definition of \( M_i(k) \) satisfying Lemma 1, as

\[
\tilde{A}_i(k)G_i = (I - K_i(k)C_i)(I - G_iM_i(k)C_i)G_i = 0.
\]

The influence of the physical interconnections of \( S_i \) is therefore decoupled from the estimation error \( \epsilon_i^h(k) \).

As the state \( x_i \) is not directly available, the residual error \( r_i \) must be used to analyze detection properties. By exploiting the decomposition of \( \epsilon_i \) in healthy and attacked parts, and using the definition of the residual (6b) and the estimation error under nominal conditions as given in (7), we obtain:

\[
r_i(k) = \hat{y}_i(k) - C_i\hat{x}_i(k) = C_i\epsilon_i^h(k) + v_i(k)
\]

\[
= C_i\tilde{A}_i(k)\left[A_i\epsilon_i^h(k-1) + w_i(k-1)\right] - C_i\tilde{L}_i(k)v_i(k).
\]

**Proposition 2:** Let an attacker carry out a covert attack as defined in (2) for time \( k \geq k_a \), with \( x_i^a(k_a) = 0 \), and let Assumption 1 hold. The residual \( r_i(k) \) is not affected by the covert attack and hence cannot be used to detect it.

Let the estimation error be defined as \( \epsilon_i \doteq x_i - \hat{x}_i \). Although a covert attack (2) on \( S_i \) does not influence the local residual \( r_i \), the same cannot be said about the estimation error. This will be exploited further in Sections V and VI to define a residual and a suitable statistical test that enables the detection of covert attacks.

A. State estimation error statistics

We analyze the mean and variance of the residual terms, in order to define a suitable detection strategy. We initialize \( \hat{x}_i(0) = \hat{x}_i^0, \forall i \in \mathcal{N} \), and we note that \( \epsilon_i(k) = \epsilon_i^h(k), \forall k \leq k_a \) holds in healthy conditions. Given
the estimates’ unbiasedness property defined in Lemma 1, the mean of the estimation error before the attack occurs is:

\[ \mathbb{E}[\epsilon_i(k)] = 0, \forall k \leq k_a, \]

while \( \mathbb{E}[\epsilon_i^h(k)] = 0 \), for all \( k \geq 0 \). Similarly, the expected value of the residual is \( \mathbb{E}[r_i(k)] = 0, \forall k \geq 0 \).

We derive the variance matrix \( \Pi_i(k) = \text{Var}(\epsilon_i(k)) \) for the estimation error, initializing it as \( \Pi_i(0) = \Pi_i^0 \):

\[
\Pi_i(k) = \bar{A}_i(k) A_i(k-1) A_i^T(k) T + \bar{A}_i(k) W_i A_i^T(k) + \bar{L}_i(k) V_i L_i^T(k) T
\]

(9)

where the covariance terms \( \text{Cov}(\epsilon_i(k-1), w_i(k-1)) \) and \( \text{Cov}(\epsilon_i(k-1), v_i(k)) \) have been omitted, as \( \epsilon_i^h(k-1) \) is uncorrelated to \( w_i(k-1) \) and \( v_i(k) \).

For \( k > k_a \), i.e. after the occurrence of the attack, the estimation error is \( \epsilon_i = x_i^a + x_i^b - \hat{x}_i = x_i^a + \epsilon_i^h \), and as such its mean is given by:

\[
\mathbb{E}[\epsilon_i(k)] = \mathbb{E}[x_i^a(k)] + \mathbb{E}[\epsilon_i^h(k)] = x_i^a(k), \forall k > k_a. \tag{10}
\]

As the attack strategy in (2) is considered to be deterministic, it will not affect the variance \( \Pi_i(k) \). Furthermore, although the estimation error mean is affected by the attack, the expected value of \( r_i \) does not change, in line with Proposition 2.

V. ESTIMATION OF COUPLING EFFECTS

As covert attacks cannot be detected using only local estimates, we exploit the communication between \( D_i \) and its neighbors to detect them in \( S_j, j \in N_i \). Specifically, we analyze the error between the unknown input estimate (5b) and that computed from the received estimates \( \hat{x}_j(k) \) computed by \( D_j \) \( \hat{x}_j(k-1) \). The corresponding error is:

\[
\rho_i(k-1|k) = \xi_i(k-1) - \hat{\xi}_i(k-1) \]

\[
= -M_i(k) C_i(A_i \epsilon_i(k-1) - w_i(k-1)) \tag{11}
\]

which holds by virtue of Lemma 1. This estimation error therefore depends only on local noise and uncertainties, as \( \epsilon_i(k) \) is decoupled from the neighboring subsystems.

Given Lemma 1, the estimate \( \hat{x}_i(k) \) is unbiased by construction. Thus it is easy to see that

\[
\mathbb{E}[\rho_i(k-1|k)] = 0. \tag{12}
\]

As far as the variance is concerned, from the definitions of the variance matrix (9), it follows that it is possible to evaluate \( \text{Var}(\rho_i(k-1|k)) \) as:

\[
\Delta_i(k-1|k) = M_i(k) C_i A_i(k-1) A_i^T(k) M_i^T(k) + 0
\]

\[
= M_i(k) C_i W_i C_i^T M_i^T(k) + M_i(k) V_i M_i^T(k). \tag{13}
\]

As \( \rho_i(k-1|k) \) is unavailable to \( D_i \), it cannot be used to detect an attack in \( S_j, j \in N_i \). Instead, supposing that \( D_i \) receives the estimates \( \hat{x}_j(k) \) from the neighbors’ diagnosis units \( D_j, \forall j \in N_i \), it is possible to locally define

\[
\hat{\rho}_i(k-1|k) = \hat{\xi}_i(k-1) - \bar{E}_i \text{col}_{j \in N_i} [\hat{x}_j(k-1)]
\]

that can be regarded as a distributed estimate of the unknown-input estimation error, which may be used for detection. From (14) and (11), we obtain:

\[
\hat{\rho}_i(k-1|k) = \bar{E}_i \text{col}_{j \in N_i} [\epsilon_j(k-1)] - \rho_i(k-1|k). \tag{15}
\]

Proposition 3: Let Lemma 1 hold. When there are no attacked subsystems \( S_j, j \in N_i \), the residual \( \hat{\rho}_i(k-1|k) \) follows a Gaussian distribution with mean and variance \( \mu_i(k) \) and \( \Sigma_i(k) \), respectively, where

\[
\mu_i(k) = 0,
\]

\[
\Sigma_i(k) = \bar{E}_i \text{diag} \left[ \Pi_j(k-1) \right] \bar{E}_i^T + \Delta_i(k-1|k). \tag{16a}
\]

\[\text{Proof:} \] Let us examine the expected value of \( \hat{\rho}_i(k-1|k) \). Let Subsystem \( S_i, l \in N_i \) be under attack starting from \( k = k_a > 0 \); then, it follows from (10), (12), and (15) that the mean \( \mu_i(k) = \mathbb{E}[\hat{\rho}_i(k-1|k)] \) is given by:

\[
\mu_i(k) = \begin{cases} 0, & k \leq k_a, \\ \zeta_i^a(k-1), & k > k_a. \end{cases} \tag{17}
\]

where

\[
\zeta_i^a(k-1) = E_i \text{col} [x_i^a(k-1)].
\]

Here, with some abuse of notation, \( E_i \text{col} [x_i^a(k-1)] \in \mathbb{R}^{n_x \times n_t} \) defines the block of row matrix \( E_i \) corresponding to \( S_i \).

For what concerns the variance \( \Sigma_i(k) = \mathbb{E}[\hat{\rho}_i(k-1|k)] \), from the definition of \( \text{Var}(\hat{\rho}_i) \) and (15) it follows that:

\[
\Sigma_i(k) = \bar{E}_i \text{diag} \left[ \Pi_j(k-1) \right] \bar{E}_i^T + \Delta_i(k-1|k), \tag{16b}
\]

where the covariance terms satisfy \( \text{Cov}(\epsilon_j, \hat{\rho}_i) = 0 \), since the estimator error \( \epsilon_i \) is independent of neighboring states by construction, for all subsystems \( S_i, i \in N \).

It is important to recall that since \( x_i^a(k) \) is deterministic, it will not influence the variance of either the estimation error or the residual. Hence, we focus on the estimation error mean. Also note that the residual variance \( \Sigma_i(k) \) can be computed locally at subsystem \( S_i \), provided that the neighbors’ process and measurement covariance matrices \( W_j \) and \( V_j \), and models \( (A_j, C_j, G_j) \) are known to \( D_i \).

VI. DETECTION STRATEGY

In this section we exploit the known statistical properties of the residual \( \hat{\rho}_i \), to design a statistical test apt at raising an alarm when suitable conditions are satisfied.

We consider a residual sequence of finite length \( \omega_i \), containing samples of \( \hat{\rho}_i(k-1|k) \) from \( k - \omega_i + 1 \) to \( k \):

\[
\{\hat{\rho}_i(k-1|k)\}_{k = k-\omega_i+1}^{k}.
\]

The following composite hypothesis test can be formulated. The null hypothesis \( H_0^i \) represents the healthy case when no subsystem \( S_j, j \in N_i \) is under attack, whereas the alternative hypothesis \( H_1^i \) holds otherwise.

Problem 2 (Covert Attack Detection): The detection logic in \( D_i \) accepts one of the following hypotheses:

\[\mathcal{H}^i_0: \hat{\rho}_i(k-1|k) = \tilde{\rho}_i^h(k-1|k),\]

\[\mathcal{H}^i_1: \hat{\rho}_i(k-1|k) = \rho_i^h(k-1|k) + \zeta_i^a(k-1), \tag{18}\]
given the estimation residual \( \hat{\rho}_i(k - 1|k) \) defined in (14). Again, the superscript \( h \) denotes the component not affected by the attack, \( \xi_{nl}(k) \) is considered to be unknown, and \( \hat{\rho}^h_i \) follows the statistic properties in (16).

**Proposition 4:** If \( M_i(k) \) is defined according to Lemma 1, and \( V_i > 0 \), then matrix \( \Sigma_i(k) \) is invertible for all \( k \geq 0 \).

Problem 2 is equivalent to detecting an unknown signal embedded in white Gaussian noise, and as such a solution can be found by means of a Generalized Likelihood Ratio test (see for instance [20]). Hypothesis \( \mathcal{H}^1 \) is accepted when

\[
p(\hat{\rho}_i(k - 1|k) | \mathcal{H}^1) = \frac{p(\hat{\rho}_i(k - 1|k) | \mathcal{H}^0)}{p(\hat{\rho}_i(k - 1|k) | \mathcal{H}^1)} \tag{19}
\]

is greater than a threshold to be defined, where \( \hat{\xi}_{nl}(k) \) is a maximum likelihood estimate of \( \xi_{nl} \). Because of whiteness of \( \hat{\rho}_i(k), \xi_{nl}(k - 1) = \hat{\rho}_i(k - 1|k) \) is such an estimate.

Let us define the statistic \( T(\hat{\rho}_i, k) \) as the logarithm of (19) and \( \theta_i(k) \) as a detection threshold, then we obtain the following detection test:

\[
\sum_{k = k - \omega_i + 1}^{k} \hat{\rho}_i(k - 1|k) \sum_{k = k - \omega_i + 1}^{k} \hat{\rho}_i(k - 1|k) > \theta_i(k), \tag{20}
\]

where it is sufficient for any component of (20) to satisfy the inequality for detection to occur. The probabilities of false alarm and detection are defined as the following:

\[
P_f^i(k) = \Pr\{T(\hat{\rho}_i, k) > \theta_i(k); \mathcal{H}^0\},
\]

\[
P_d^i(k) = \Pr\{T(\hat{\rho}_i, k) > \theta_i(k); \mathcal{H}^1\}. \tag{21}
\]

Since \( \Sigma_i(k) \) is symmetric positive definite it is possible to find \( U_i(k) \) orthogonal such that \( \Sigma_i(k) = U_i(k)\Lambda_i(k)U_i^T(k) \), with \( \Lambda_i(k) \) diagonal. Thus, a transformation

\[
\hat{z}_i(k) = U_i(k)\hat{\rho}_i(k)
\]

can be defined, where the components of \( \hat{z}_i \) are mutually uncorrelated and each \( q \)-th component has variance \( \lambda_{i[q]}(k) \). Therefore, for \( q \in [1, g_i] \), we have that, for threshold \( \hat{\theta}_{i[q]}(k) \):

\[
T'(\hat{z}_{i[q]}, k) = \sum_{k = k - \omega_i + 1}^{k} \hat{\rho}_{i[q]}(k - 1|k) > \hat{\theta}_{i[q]}(k). \tag{22}
\]

Since \( \hat{z}_i \) is linearly related to \( \hat{\rho}_i \), and in light of (17), \( T'(\hat{z}_{i[q]}, k) \) follows the distribution:

\[
T'(\hat{z}_{i[q]}, k) \sim \begin{cases} 
\chi^2_{\omega_i}(0) & \text{if } \mathcal{H}^0, \\
\chi^2_{\omega_i}(\nu_q) & \text{if } \mathcal{H}^1,
\end{cases} \tag{23}
\]

where \( \chi^2(\nu_q) \) is a chi-squared distribution with degree of freedom \( \omega_i \) and non-centrality parameter

\[
\nu_q = \sum_{k = k - \omega_i}^{k - 1} \frac{1}{\lambda_{i[q]}(k)} \left( U_{i[q]}(k)\xi_{i[q]}(k) \right)^2, \tag{24}
\]

where \( U_{i[q]}(k) \) denotes the \( q \)-th row of matrix \( U_i(k) \). Let us define the tail probability of the normalized \( \chi^2 \) distribution as

\[
\Phi(u) \triangleq 1 - \Pr\{T'(\hat{z}_{i[q]}, k) < u\}. \tag{25a}
\]

\[
P_f^{i[q]}(k) = \Phi \left( \frac{1}{\sqrt{2\omega_i}} \left( \tilde{\theta}_{i[q]}(k) - \omega_i \right) \right) \tag{25b}
\]

\[
P_d^{i[q]}(k) = \Phi \left( \frac{\sqrt{2k} \Phi^{-1}(P_f^{i[q]}(k)) - \nu_q}{\sqrt{4\nu_q + 2\omega_i}} \right). \tag{25c}
\]

**Remark 5:** Note that \( T'(\hat{z}_{i[q]}, k) \) represents the energy of the attack received by \( S_i \). From (25b) it can be seen that the probability of detection decreases as the attack energy decreases. Furthermore, as \( \nu_q \to 0 \), the probability of detection approaches that of false alarm. More precisely, \( \nu_q \) depends on the energy of the attacked state \( x_i^n \) as scaled by the corresponding interconnection weight.

Also, note that the presence of the input estimate variance \( \lambda_{i[q]}(k) \) reduces the effect of the attack on \( \nu_q \).

Eqs. (25a) and (25b) hold component-wise. It is possible to find an expression for the probability of false alarm \( P_f^i(k) \) of detector \( D_i \) by observing that the probability of at least one false alarm is the complementary to the probability of no false alarms. Thus, recalling that the components of \( \hat{z}_i \) are independent by construction, we have:

\[
P_f^i(k) = 1 - \prod_{q = 1}^{g_i} \left( 1 - P_f^{i[q]}(k) \right). \tag{26}
\]

If we assume the same probability \( P_f^{i[q]}(k) \) for each component \( q \), it is possible to invert (26) and (25a). This allows to compute individual thresholds \( \hat{\theta}_{i[q]} \), given a desired cumulative probability \( P_f^i(k) \). The overall probability of detection can be found in the same way, although it depends on \( \nu_q \).

**VII. NUMERICAL SIMULATIONS**

A. Simulation setup

We consider a CPS composed of \( N = 4 \) subsystems, interconnected as in Figure 1. We consider the linearized model of multiple pendula coupled through a spring, as presented in [21, Ex. 1.36], where each subsystem is described by:

\[
m_i \ddot{x}_i = m_i g l_i \dot{\delta}_i + u_i + \sum_{j \in \mathcal{N}_i} k_{ij} a_i^2 (\delta_j - \delta_i), \tag{27}
\]

where \( \delta_i, m_i, l_i \) are respectively the displacement angle, mass, and length of the pendulum; \( g \) is the gravitational constant; \( k_{ij} \) is the spring coefficient, with \( k_{ij} = k_{ji} \), and \( a_i \) is the height at which the spring is attached to pendulum \( i \).

The parameter values used in the numerical simulation can be found in Table I.

Choosing \( x_i \triangleq [\delta_i, \dot{\delta}_i]^T \), and defining a decentralized state feedback control law \( u_i = K_i x_i \), we discretize the pendulum’s dynamics subsystem-by-subsystem with Euler’s approximation with sampling time \( T_s = 0.01 \) s, preserving the topology and the interconnection structure of the CPS. For all subsystems, we assume that all states are measurable, i.e. \( C_i = I_3 \). The process and measurement noise variance matrices are \( W_i = 10^{-3} I_3 \) and \( V_i = 10^{-3} I_3 \). We run the simulation for 100 s.
Fig. 2: Comparison of the statistic $T'(\hat{z}_i,k)$, in blue, against the detection threshold $\bar{\theta}_i(k)$, in dashed-black.

### TABLE I: Subsystem and interconnection parameters

| $m_i$ | $l_i$ | $a_i$ | $k_{12}$ | $k_{23}$ | $k_{24}$ | $k_{34}$ |
|------|------|------|---------|---------|---------|---------|
| 0.5 kg | 0.1 m | 0.06 m | 27 | 40 | 35 | 53 |

From (27), and considering the Euler approximation for the discretization of each subsystem, it is possible to choose $G_i = [0,1]^T$. Note that $\xi_i \in \mathbb{R}$, for all subsystems.

### B. Attack scenario and detection

Starting from time $k_a = 35$ s, an attacker is able to inject

$$\eta_3(k) = 0.5 \left(1 - e^{-0.3(k-T_a-k_3)}\right) \sin \left(\frac{2}{30} \pi k \cdot T_s\right),$$

where the attenuation term $(1 - e^{-0.3(k-T_a-k_3)})$ is added to reduce the transient behavior of the attack. In Figure 2, we show the effectiveness of our detection technique, by comparing the statistic $T'(\hat{z}_i,k)$, computed by using a window of size $\omega_i = 20$, to the threshold $\bar{\theta}_i(k)$, defined for all subsystems such that the probability of false alarm $P_f^I = 0.05$.

At time $k = 36.78$ s, detector $D_2$ detects the presence of an attack in $N_2$, while $D_4$ detects the attack in $N_4$ at time $k = 37.16$ s. As expected, the diagnosers for subsystems $S_1$ and $S_3$ do not detect an attack.

### VIII. Concluding Remarks

We have proposed a distributed method capable of detecting local covert attacks in interconnected CPSs with stochastic uncertainties. The proposed method is based on the joint estimation of local states and the neighbors’ cumulative effect; communication among subsystems enables definition of a suitable residual signal and a related statistical test.

Future work will include studying additional detectability properties of the proposed approach and comparison to other techniques for solving Problem 2, as well as investigation into the architecture’s robustness to other types of attacks.

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