

Privileged Estimate Fusion With Correlated Gaussian Keystreams

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Abstract—Providing cryptographic privacy guarantees in a distributed state estimation problem has been a growing topic of research since the ubiquity of modern public networks. One such guarantee is having different levels of estimation performance achievable by trusted and untrusted users within a sensor network. In the presence of multiple sensor measurements, guaranteeing better estimation performance by the usual means of adding removable noise to measurements is complicated by an alternative for untrusted users to improve their performance: fusing more measurements. Our novel method adds correlated noise at different sensors, restricting the performance gained from fusing additional measurements while guaranteeing better performance to those that can remove it. We extend a cryptographic framework for defining estimation privilege and use this to prove the scheme’s security goals, while simulations demonstrate the effects of parameters in a concrete estimation problem. A scheme that can ensure such differences in estimation performance between types of estimators can find applications in priority-based or subscription-based performances in environments where more than one sensor is present.

I. INTRODUCTION

Sensor data processing and state estimation have long been active areas of research and continue to find applications in modern systems [1], [2]. In the context of distributed sensing environments such as decentralised autonomous vehicles or distributed weather stations, estimation methods relying on Kalman filters and derivatives [3] are particular prevalent due to their recursive, often optimal, estimation properties and their suitability to modelling measurement cross-correlations typically required for data fusion [4], [5]. In recent years, the ubiquity of distributed public networks has seen the additional requirements of preserving algorithm participants’ privacies, such as individual contributions or identifying information, become increasingly relevant and has led to an active field of research [6], [7].

While hiding transmitted information to eavesdroppers can be achieved using common encryption schemes that make ciphertexts indistinguishable [8], distributed estimation tasks that preserve participants’ privacies require information to remain hidden during partial or complete processing of the task and often justify some leakage [9], [10]. The security goals of these problems are context-specific and have produced a variety of solutions. In [11], non-Bayesian localisation is

performed using homomorphic encryption such that individual sensor information and measurements remain private, while in [12], similar goals are achieved in a Bayesian setting by fusing linear measurements when sensors form a hierarchical network. A combination of homomorphic and order-revealing encryption schemes are used in [9] to solve conservative Gaussian estimate fusion while leaking only the ratios of estimate covariances, and in [10], [13], cryptographic aggregation schemes are introduced and used to leak only total consumptions in an energy grid while hiding individual participant power-usages. In addition to these examples of privacy, achieved through hiding and leaking quantifiable information, optimal estimation performance itself can be considered leakage, which introduces a privilege in estimation where leakage defines the difference in performance between trusted and untrusted estimators. In the original Global Positioning System (GPS) [14], this was achieved with a secondary encrypted channel that allowed better estimation performance to parties that held an encryption key. Similarly, in [15], a synchronised chaotic system is used to add noise to measurements which can only be removed by estimators knowing its properties. This idea of estimation privilege is further explored in [16], where a formal cryptographic definition is given and a scheme for a single sensor presented. Here, a synchronised pseudorandom Gaussian keystream adds measurement noise only removable by estimators holding the stream key.

In this work, we consider this definition of estimation privilege, presented in [16], and introduce a modified scheme suitable for an environment of multiple sensors, where both holding the secret key and fusing additional measurements can lead to better estimation performance. Our contribution consists of a generalised notion of estimation privilege, the introduction of security requirements for privileged estimation in a well defined multisensor environment and a scheme that satisfies them. Along with a cryptographic proof sketch, simulation results are provided to demonstrate the effects of scheme parameters and how they can be chosen to provide varying amounts of privilege. Use-cases for varying performance in this way include subscription or priority models where some users are provided better results than others. For example, subscription-based weather forecasts using measurements from

spatially distributed stations or modular mass-produced sensors that differ in accuracy dependent on cost.

In section II, the multisensor estimation privilege problem is presented. Relevant preliminaries are introduced in section III and the estimation privilege fusion scheme itself in section IV. A cryptographic analysis and the simulation results are then given in sections V and VI, respectively, before the concluding remarks in section VII.

A. Notation

- Matrices, vectors.
- Positive definiteness.
- Pseudorandom distribution.
- Estimator in cryptographic sense.
- Negligible fuction and negligible covariance.

II. PROBLEM FORMULATION

We are interested in environments where multiple sensors are present and the fusion of their measurements can lead to better state estimation accuracy of the system they are measuring. In these environments, we want to provide levels of privilege to state estimators such those with a higher privilege can perform better than those with a lower one, while taking into consideration the estimation benefits from fusing additional measurements. We will consider linear and Gaussian models, where a state $\underline{x}_k \in \mathbb{R}^n$ at an integer timestep k , follows a system model given by

$$\underline{x}_k = \mathbf{F}_k \underline{x}_{k-1} + \underline{w}_k, \quad (1)$$

with white noise term $\underline{w}_k \sim \mathcal{N}(\underline{0}, \mathbf{Q}_k)$ and a known covariance $\mathbf{Q}_k \in \mathbb{R}^{n \times n}$. Similarly, measurements $\underline{y}_{k,i} \in \mathbb{R}^m$ from each sensor i , $1 \leq i \leq N$, follow the measurement models

$$\underline{y}_{k,i} = \mathbf{H}_{k,i} \underline{x}_k + \underline{v}_{k,i}, \quad (2)$$

with white noise term $\underline{v}_{k,i} \sim \mathcal{N}(\underline{0}, \mathbf{R}_{k,i})$ and a known covariance $\mathbf{R}_{k,i} \in \mathbb{R}^{m \times m}$. In addition to these models, we assume that all sensors i are synchronised in timesteps k to simplify later cryptographic evaluation. In practice, this would restrict the presented schemes to scenarios where synchronisation is easier to guarantee, such as ones where measurements are taken infrequently.

Each of the sensors also holds a secret key sk_i , which can be made available to estimators of appropriate privilege. The privileges that we consider, in terms of access to keys and measurements, will be defined by sequential sensors. That is, in the presence of N sensors, we consider exactly N possible privilege levels, where each privilege $p > 0$ corresponds to holding the sequential secret keys sk_j , $1 \leq j \leq p$ while being unprivileged, $p = 0$, corresponds to holding none. We assume that estimators have access to all “privileged measurements”, those from sensors whose keys they hold, and can additionally fuse “unprivileged measurements” from those whose keys they do not hold. We can therefore capture their capabilities by letting $e_{p,q}$ denote an estimator with privilege p and access to measurements from $q \geq p$ sensors, $1 \leq i \leq q$.

To cryptographically guarantee the difference between estimation performances, we will use the notion of covariance privilege introduced in [16] and given in section III. As we want better performance for higher privilege estimators as well as to limit the gained performance from fusing unprivileged measurements, two differences will be considered.

Different Keys First, we want to guarantee a lower bound on the difference between the best unprivileged estimator $e_{0,N}$ and the best privilege- p estimator $e_{p,p}$. This will, therefore, remain a lower-bound when unprivileged estimators have access to fewer unprivileged measurements or privileged estimators have access to more.

Same Keys Second, we want to guarantee an upper bound on the difference between the best privilege- p estimators $e_{p,p}$ and $e_{p,N}$. Here, the bound remains an upper bound on the gained estimation performance of any privilege- p estimator fusing additional unprivileged measurements.

The resulting scheme should be such that two parameters are responsible for choosing the values of these two bounds.

III. PRELIMINARIES

When defining our scheme and discussing its cryptographic guarantees, we will make use of Gaussian keystreams and the notion of cryptographic estimation covariance privilege. These have been summarised below.

A. Gaussian keystreams

A Gaussian keystream is a sequence of pseudorandom multivariate Gaussian samples $\underline{g}_k \sim \mathcal{N}(\underline{0}, \mathbf{S})$, $k > 0$, for some covariance matrix \mathbf{S} , generated using a secret key. The sequence is indistinguishable from a truly random multivariate Gaussian sequence to any observer who does not hold the key while being reproducible exactly by those that do. The keystream can be constructed from a typical cryptographic stream cipher [8, Ch. 3.6], by using any common method for random floating-point generation [17] to create a stream of pseudorandom uniform samples $u_i \sim \mathcal{U}(0, 1)$, $i > 0$. Here, we make the assumption that floating-point representations of real numbers are sufficiently similar to actual real numbers, made reasonable in practice due to the insignificance of their difference in many applications and their prevalence in estimation theory.

To construct the Gaussian keystream \underline{g}_k , $k > 0$, from the uniform one u_i , $i > 0$, a vector of uncorrelated standard Gaussian samples \underline{z}_k is first generated using the Box-Muller transform,

$$\underline{z}_k = [z_{(k-1)n+1} \quad \cdots \quad z_{kn}]^\top \quad (3)$$

where

$$z_i = \begin{cases} \sqrt{-2 \ln(u_{2i})} \cos(2\pi u_{2i+1}), & i \text{ is odd} \\ \sqrt{-2 \ln(u_{2i})} \sin(2\pi u_{2i+1}), & i \text{ is even} \end{cases},$$

and then correlated by

$$\underline{g}_k = \mathbf{A} \underline{z}_k, \quad (4)$$

where \mathbf{A} is any matrix such that $\mathbf{A} \mathbf{A}^\top = \mathbf{S}$.

B. Cryptographic Estimation Privilege

The formal definition of a privileged estimation scheme and accompanying notion of covariance privilege are introduced in [16] and capture a reduction in estimation performance that can always be achieved from a probabilistic polynomial-time (PPT) estimator knowing only unprivileged measurements, and holding no scheme key, to one knowing both the key and privileged measurements. We will use a slight generalisation of this definition to capture an arbitrary difference that can always be achieved between the estimators (rather than only a reduction). A privileged estimation scheme is defined by a pair of probabilistic algorithms (Setup, Noise):

Setup($\mathcal{M}_S, \mathcal{M}_M, \kappa$) Given system and measurement models \mathcal{M}_S and \mathcal{M}_M , and the security parameter κ , public parameters pub and a secret key sk are returned.

Noise($\text{pub}, \text{sk}, k, \mathcal{M}_S, \mathcal{M}_M, \underline{y}_1, \dots, \underline{y}_k$) Given public parameters pub , secret key sk , timestep k , models \mathcal{M}_S and \mathcal{M}_M , and measurements $\underline{y}_1, \dots, \underline{y}_k$, modified privileged and unprivileged measurements, $\underline{y}_k^{(p)}$ and $\underline{y}_k^{(up)}$, respectively, are returned.

Using the definitions from [16] for an *estimator* and *negligible covariance* $\text{neglCov}_m(\kappa)$, the notion of covariance privilege is defined as follows.

Definition 3.1: A privileged estimation scheme meets notion $\{\mathbf{D}_1, \mathbf{D}_2, \dots\}$ -Covariance Privilege for Models \mathcal{M}_S and \mathcal{M}_M if for any PPT estimator \mathcal{A} , there exists a PPT estimator \mathcal{A}' , such that

$$\begin{aligned} & \text{Cov} \left[\mathcal{A} \left(k, \kappa, \text{pub}, \mathcal{M}_S, \mathcal{M}_M, \underline{y}_1^{(up)}, \dots, \underline{y}_k^{(up)} \right) - \underline{x}_k \right] \\ & - \text{Cov} \left[\mathcal{A}' \left(k, \kappa, \text{pub}, \mathcal{M}_S, \mathcal{M}_M, \underline{y}_1^{(p)}, \dots, \underline{y}_k^{(p)} \right) - \underline{x}_k \right] \quad (5) \\ & \succeq \mathbf{D}_k - \text{neglCov}_m(\kappa) \end{aligned}$$

for all $k > 0$, some negligible covariance and where matrices \mathbf{D}_k are definite, i.e., $\mathbf{D}_k \preceq \mathbf{0}$ or $\mathbf{D}_k \succeq \mathbf{0}$. Here, \mathcal{A} and \mathcal{A}' are running in polynomial-time with respect to the parameter κ and all probabilities are taken over randomness introduced in models \mathcal{M}_S and \mathcal{M}_M , estimators \mathcal{A} and \mathcal{A}' , and algorithms Setup and Noise.

We note that in the generalised notion (5), $\mathbf{D}_k \preceq \mathbf{0}$ is allowed, and unprivileged estimators may now perform better than privileged ones, albeit by a bounded amount. This feature will be useful when discussing additional estimation performance gainable from fusing unprivileged measurements. Lastly, a sign is also corrected, such that negligible covariances are subtracted (rather than added), correctly capturing the additional negligible performance gainable by an unprivileged estimator.

IV. PRIVILEGED FUSION

The idea behind our privileged estimation fusion scheme is to add *correlated* Gaussian keystreams to the measurements from each sensor. These noises can be computed and subtracted by estimators holding respective sensor keys, while their correlation limits the additional information gained from fusing unprivileged measurements.

A. Noise Generation

Similarly to the Gaussian keystream generation in (4), pseudorandom samples can be correlated in this way even when generated using different stream cipher keys. To parameterise the correlation between noises at each sensor, we introduce a fully correlated component $\mathbf{Z} \in \mathbb{R}^{m \times m}$ and an uncorrelated component $\mathbf{Y} \in \mathbb{R}^{m \times m}$ and define a noise cross-correlation matrix for N sensors, $\mathbf{S} \in \mathbb{R}^{Nm \times Nm}$, as

$$\mathbf{S} = \begin{bmatrix} \mathbf{Z} & \dots & \mathbf{Z} \\ \vdots & \ddots & \vdots \\ \mathbf{Z} & \dots & \mathbf{Z} \end{bmatrix} + \text{diag} \left(\begin{bmatrix} \mathbf{Y} \\ \vdots \\ \mathbf{Y} \end{bmatrix} \right). \quad (6)$$

The generation of all N Gaussian noises at timestep k , $\underline{g}_k^{(N)}$, can now be written as

$$\underline{g}_k^{(N)} = \begin{bmatrix} \underline{g}_{k,1} \\ \vdots \\ \underline{g}_{k,N} \end{bmatrix} = \mathbf{S}^{\frac{1}{2}} \cdot \begin{bmatrix} \underline{z}_{k,1} \\ \vdots \\ \underline{z}_{k,N} \end{bmatrix}, \quad (7)$$

where each $\underline{z}_{k,i}$ is first computed as \underline{z}_k in (3), using uniform samples generated with cipher key sk_i , and $\mathbf{S}^{\frac{1}{2}}$ is a matrix such that $\mathbf{S}^{\frac{1}{2}} \mathbf{S}^{\frac{1}{2} \top} = \mathbf{S}$. Notably, it is important that the first p noises $\underline{g}_{k,1}, \dots, \underline{g}_{k,p}$ in (7), denoted $\underline{g}_k^{(p)}$, can be reproduced by an estimator of privilege p , holding only the keys sk_i , $1 \leq i \leq p$. When $\mathbf{S}^{\frac{1}{2}}$ is a lower-triangular matrix, as is the case when using the Cholesky decomposition of \mathbf{S} , each correlated Gaussian sample $\underline{g}_{k,i}$ is computable from preceding uniform samples only, $\underline{z}_{k,j}$, $j \leq i$. Then, the generalised noise generation equation

$$\underline{g}_k^{(p)} = \mathbf{S}^{\frac{1}{2}(p)} \cdot \begin{bmatrix} \underline{z}_{k,1} \\ \vdots \\ \underline{z}_{k,p} \end{bmatrix}, \quad (8)$$

where $\mathbf{S}^{\frac{1}{2}(p)} \in \mathbb{R}^{pm \times pm}$ is the top left block from the lower-triangular matrix $\mathbf{S}^{\frac{1}{2}}$, can be used to generate the same first p noises $\underline{g}_k^{(p)}$ as would be obtained from (7).

With (8), at every timestep k , $\underline{g}_k^{(N)}$ can be generated using all N keys and used to modify sensor measurements, while the subset $\underline{g}_k^{(p)}$ can be generated by estimators of privilege p using the only keys they hold.

B. Measurement Modification

With a way to generate noises for sensors and estimators, we can introduce the means of measurement modification and the observable measurement models for different estimators.

Measurement modification is performed by adding noises $\underline{g}_k^{(N)}$ to measurements from each sensor i before making them public, resulting in modified measurement equations for each sensor,

$$\begin{aligned} \underline{y}_{k,i}^{(up)} &= \underline{y}_{k,i} + \underline{g}_{k,i} \\ &= \mathbf{H}_{k,i} \underline{x}_k + \underline{v}_{k,i} + \underline{g}_{k,i}, \end{aligned} \quad (9)$$

where $\underline{v}_{k,i} \sim \mathcal{N}(\underline{0}, \mathbf{R}_{k,i})$ and $[\underline{g}_{k,1} \dots \underline{g}_{k,N}]^\top \sim \mathcal{N}(\underline{0}, \mathbf{S})$.

As we assume that sensors are synchronised, we can capture the correlation between modified measurements exactly by considering the stacked measurement model for an estimator $e_{p,q}$ at time k ,

$$\underline{y}_k^{(p,q)} = \mathbf{H}_k^{(q)} \underline{x}_k + \underline{v}_k^{(q)} + \underline{g}_k^{(p,q)} \quad (10)$$

where $\underline{v}_k^{(q)} \sim \mathcal{N}(\underline{0}, \mathbf{R}_k^{(q)})$ and $\underline{g}_k^{(p,q)} \sim \mathcal{N}(\underline{0}, \mathbf{S})$, with

$$\underline{y}_k^{(p,q)} = \begin{bmatrix} \underline{y}_{k,1} \\ \vdots \\ \underline{y}_{k,q} \end{bmatrix}, \quad \mathbf{H}_k^{(q)} = \begin{bmatrix} \mathbf{H}_{k,1} \\ \vdots \\ \mathbf{H}_{k,q} \end{bmatrix}, \quad \underline{v}_k^{(q)} = \begin{bmatrix} \underline{v}_{k,1} \\ \vdots \\ \underline{v}_{k,q} \end{bmatrix},$$

$$\mathbf{R}_k^{(q)} = \text{diag} \left(\begin{bmatrix} \mathbf{R}_{k,1} \\ \vdots \\ \mathbf{R}_{k,q} \end{bmatrix} \right)$$

and some cross-correlation matrix \mathbf{S} .

- The generation of the additive noise can then be computed with m standard normal pseudorandom samples generated from keys of each sensor with the following equation (using $S^{1/2}$) and added to the measurements at every timestep k as follows (give measurements equation with two noises).
- Now, an estimator of privilege j (that holds the keys sk_1, \dots, sk_j , $j \leq n$), can correctly generate the noises for sensors $1, \dots, j$ by computing (give partial generation equation up to sensor j).
- The subset of computed noises can then be removed from received sensor measurements z'_1, \dots, z'_j by subtracting it.
- Since we are using a cryptographically sound stream cipher, pseudorandom Gaussian samples are indistinguishable from truly random ones to an estimator not holding any relevant keys. We can then consider three estimation problems.
- First, an estimator with access to j sensors and no keys (unprivileged estimator) will have measurements indistinguishable from those following the measurement model given by (model but with additional measurement noise Y and Z).
- Second, an estimator with privilege j and access to the first j sensors $1, \dots, j$ can remove all added pseudorandom noise from observable measurements and follows the measurement model given earlier exactly.
- Lastly, an estimator with privilege j and access to the first j sensors $1, \dots, j$ as well as some additional l remaining sensors. In this case, noises can be removed from the first j measurements, while the remaining l measurements have conditional Gaussian noise based on the first j pseudorandom samples. This can be captured by the measurement equation (give slightly more complicated conditional measurement equation that will not have zero-mean noise).
- Intuitively, and from the measurement models observed for the different estimators above, we can tell that the

parameters Z and Y will control the difference in estimation performance between estimators.

- More specifically, the fully correlated term Z will control the difference in estimation between an unprivileged and privileged estimator, while the uncorrelated term Y will control the difference in estimation between privileged estimators with and without access to additional measurements from sensors to which they do not hold keys.
- These two differences correspond to the two guarantees we want to show for the presented scheme (introduced in the problem formulation section).
- The effects of choosing these parameters will be formally explored in the cryptography section.

C. Noise Distribution

- While we have described a method for generating noise for n sensors such that different estimators observe different measurement models being followed, we have not discussed where noise is generated and how it is distributed to the relevant sensors.
- Due to the correlation between sensor noises in the method above, the generation of one sensor's noise is dependant on generated noise from others. To handle this, they can be generated either centrally and distributed to sensors or sequentially by the sensors 1 through n .
- To compute them centrally, equation (generation of n noises given before) is computed by a central processor and each noise $p_{i,k}$, $1 \leq i \leq n$, is sent to sensor i to add to their measurement at time k .
- Sequentially, each sensor can generate its own noise $p_{i,k}$ based on the noises generated before it, that is, given $p_{j,k}$, $1 \leq j < i$, the conditional Gaussian can be computed as (equation for generating sequential correlation). However, a downside of this method is the increasing size of data being sent to each sensor as the noise is generated and can result in later sensors requiring more processing power than may be available.
- In both of the cases, however, the computation of noises $p_{i,k}$ can be done offline and in advance, such that sensors have sufficient additive noises already computed prior to commencement of measurement.

V. CRYPTOGRAPHIC PRIVILEGE

- To give a sketch proof of the cryptographic privilege provided by the presented multisensor scheme, we first recall two important assumptions. We consider cryptographically generated random floating-point numbers to be sufficiently close to real numbers that real number proofs can be used, namely the optimality of the Kalman filter, and that all sensors are synchronised, such that noises $p_{i,k}$ are always added to measurements $z_{i,k}$ from each sensor and that the measurement stacked model (given at the start of the scheme section) is correct for all k .
- The sketch proof will rely on the optimality of the linear Kalman filter to produce a series of covariances

that are the best achievable (smallest possible) for given estimators and take the difference between estimators in question to bound their difference and achieve cryptographic estimation privilege.

- Similarly to the previous paper, the bounding series can be used in a cryptographic sketch proof which shows that the existence of an estimator violating the bound would imply the existence of a better linear estimator than the Kalman filter, known not to exist. This then guarantees the bound by contrapositive.
- We consider two types of unprivileged estimation which we want to bound, namely estimators holding no keys and estimators holding only a subset of keys, as specified in the desired guarantees.

A. Unprivileged Adversaries

- If we assume an unprivileged estimator can access all n sensors, then their stacked estimation model can be described by the appropriate equation at each timestep k .
- We can then write the combined Kalman predict and update equation as the equation with params from the previous one.
- Due to the KF preserving error covariance order, by setting $P_0 = 0$ we get a series of covariance such that no unprivileged estimator can estimate with error covariances less than or equal to the series (lower-bound).
- Similarly we can do the same for an estimator to which we want to lower-bound the estimation difference with the unprivileged estimator.
- A privileged estimator of privilege j (access to the first j keys) and that can only access the first j sensors, has the appropriate measurement equation. Similarly, setting the initial covariance to zero gives the lower bound series on the best possible estimation error achievable by the privileged estimator using only the measurements from the sensors to which it holds keys.
- Taking the difference of the two estimator bounding series' produces the difference series.
- In the context of cryptographic privileged estimation scheme, the Setup and Noise algorithms are given accordingly. The optimality of the KF can then be used to achieve the security notion.
- In the above, we assume the unprivileged estimator has access to all n sensors, while the j privilege estimator has access to only the first j sensors. In the case when the unprivileged estimator has access to fewer sensors or the privileged one to more, their difference in estimation can only increase, thus keeping the computed lower-bound a lower-bound and the cryptographic guarantee does not change (albeit the definitions of Setup and Noise will, to capture the now available sets of measurements).

B. Privileged Adversaries

- We can use a similar approach to separately guarantee the largest possible benefit in estimation available to an estimator of privilege j (access to first j keys) when

fusing measurements from sensors to which they do not hold keys to get a better state estimate.

- We can again write stacked estimation models for the two estimators. The estimator of privilege j with access to the first j measurements still follows the model (given in the previous subsection).
- The estimator with access to the additional l measurements, however, does not have zero-mean measurement noise as seen in (equation for the additional measurements estimator given before) required for the Kalman filter. As the mean is known at each k , from the known noises $p_{i,k}$, $1 \leq i \leq j$, remaining measurements can be offset to produce the equivalent measurement model with zero-mean noise (given here).
- Again, using the combined predict and update equations of the KF and setting $P_0 = 0$, we can use the optimality of the KF to give the best possible performances of the estimators as a series of covariances.
- Taking the difference of the bounds now gives a bound on how much better an estimate can become when unprivileged measurements are fused with privileged ones.
- In the context of a cryptographic privileged estimation scheme, the Setup and Noise algorithms can be given as follows. KF optimality can then be used to achieve the security notion.
- We note that unlike in the unprivileged adversary case, or the previous paper, here we do not use unmodified measurements for the privileged estimates and the resulting algorithms provide better estimation for the adversary than the privileged estimator. In this form, we bound how much better an adversary can estimate when using unprivileged estimates resulting in series D_k consisting of negative-definite rather than positive definite matrices. This makes use of the generalised cryptographic definitions earlier.

VI. SIMULATION

- In addition to showing how to derive the bounds to the benefits of using unprivileged measurements, we have simulated concrete scenarios to demonstrate the methods.
- We consider the following linear system, and linear measurement models for 4 sensors. Correlated and uncorrelated noise covariances are of the form $Y = \sigma_y I$ and $Z = \sigma_z I$.
- Implementation details.
- First figure shows 4 plots. Each plot shows three traces. The traces are the trace of the unprivileged estimator (no keys, all measurements), the trace of a privilege j estimator (j measurements) and the trace of a fusing privilege j estimators (all measurements). j is equal to 1, 2, 3 and 4 for each plot, respectively. Here, the difference between the first two traces in figure 4 and the second two traces in figure 1 is equal to the traces of the two D_k series from the cryptography section, respectively. Values for σ_y , σ_z are fixed.

- The second figure focuses on a single plot from the first figure but varies σ_y and σ_z . Again, 4 plots are shown, with σ_y increased in two and σ_z increased in two, such that they are both increased in only one plot. This will show that while both parameters affect the estimation of unprivileged and additional fusion estimators, σ_y and therefore Y predominantly affects the unprivileged estimator and σ_z , Z , affects the additional fusion estimator.

VII. CONCLUSION

- Concluding remarks.
- Future work includes exploring key subsets that do not need to be sequential, decentralised methods for multi-key correlated noise generation, and the effects and cryptographic guarantees of sensors falling out of synchronisation.

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