Multi-Target Signal Estimation with Sensor Networks under Imperfect CSI

Vimal Radhakrishnan, Ehsan Zandi, Omid Taghizadeh, and Rudolf Mathar
Institute for Theoretical Information Technology, RWTH Aachen University, Germany
Email: {radhakrishnan, zandi, taghizadeh, mathar}@ti.rwth-aachen.de

***Abstract*—This paper solves the problem of multi-target signal estimation with the aid of sensor networks, given the condition that the channel state information is imperfect. First, an unbiased estimator is proposed. Subsequently, the variance of the estimation error is minimized by optimal data the fusion at fusion center. Moreover, the power allocation to different sensors is optimized, in order to extend the lifespan of the network. The incentive to do so is that, we assume that the sensors are battery operated. This makes the optimal power allocation crucial for a prolonged lifespan.**

***Index Terms*—optimal fusion, target detection, classification, state estimation, separable targets**

I. Introduction

With the conception of the internet of things (IoT), sensor networks are gaining utmost importance. The reason is simple: IoT depends on awareness and awareness relies on collecting information with the aid of wireless sensor networks (WSNs). This entwines IoT and WSN, both of which have been hot research topics, as well as investment areas, in the last two decades. The applications of WSN range from *environmental monitoring*, *health care*, *industrial monitoring*, *military applications*, and so on [1].

Usually WSN refers to a group of low cost, low data rate and low power sensors which share their observations to make up a centralized, intelligent entity. One of the main challenges of sensor networks is manufacturing low cost, tiny and low power sensor nodes. Typically, a sensor node (SN) is comprised of five main components, namely controller, transceiver, memory, power source, and sensor unit. Nonetheless, recent advances in the area of micro-electro-mechanical system, known as MEMS, have enabled fabricating sensor nodes in the size range of a micron to a few millimeters [2]. The sensor unit of an SN includes one or more sensors to measure different physical quantities, such as temperature, humidity, pressure, inertial forces, magnetic field, and chemical species. The number of companies in the industry of sensor production is increasing, leading to the existence of low price sensors in the market. Availability of such sensors low-cost motivates the implementation of sensor networks for different purposes.

Such use cases have been successfully presented, e.g., in [3]–[7] for bi- and multi-static radars. In particular, applications of a system of passive distributed radar have been exemplified in [4] in the context of remote surveillance and in [7] addressing a high resolution 3D imaging problem.

As an interesting implementation, we can mention the '*Ice-Cube Neutrino Observatory*' at the south pole, where a sensor network with more than 5000 SNs is deployed to observe certain characteristics of sub-atomic particles [6]. Since the operation of the whole sensor network is mostly intended to consume minimum resources, while keeping the individual cost and maintenance of SNs low, an energy efficient operation is highly desirable. Hence, the related problem of optimal power allocation and its corresponding energy -aware system design has been addressed in the recent literature, e.g., in [8]–[10]. Nevertheless, the aforementioned works focus on a radar system with a single active source. In [11]–[17] the system of distributed sensor network is considered for a setup with multiple simultaneously active sources, i.e., targets. The main focus areas include the problems related to coverage, target localization and tracking. Please note that the availability of multiple sensing and fusion paths in a distributed SN system, accommodates the joint observation and separation of multiple simultaneously active targets. This is necessary, when the source signals may not be separated at the individual SNs or a low-delay estimation is required. Moreover, such an operation is gainful in terms of resource expenditure, as the interfering sensing signal from the multiple co-existing targets, will be treated as useful signals to enable a joint estimation at the fusion center (FC). This result in a fewer required sensing and communication resources for the overall observation or estimation process. In this regard, the work in [11] focuses on maximizing the lifetime subject to power constraints and coverage regions. In the present work we minimize the estimation error instead of maximizing the lifetime. The authors in [12] use the GaussMarkov mobility model to formulate the tracking problem as a hierarchical Markov decision process and is solved with the aid of neurodynamic programming.

The optimal allocation of resources such as energy, power are important to these systems as the estimation performance are dependent on it. In WSNs the sensors are usually battery-operated, which makes the power consumption crucial. Low complexity signal processing and decision making strategies also become critical to reduce the power consumption for battery replacement is not only time consuming and costly, but also impossible in some applications. Therefore, many studies are done in the literature, mainly for a single target signal [18]. In [19] the performance bound of a wireless sensor network is studied, which is capable of estimating the true values of several active orthogonal targets. An unbiased estimator is proposed assuming perfect channel state information (CSI) is available. This assumption is not practical in many related

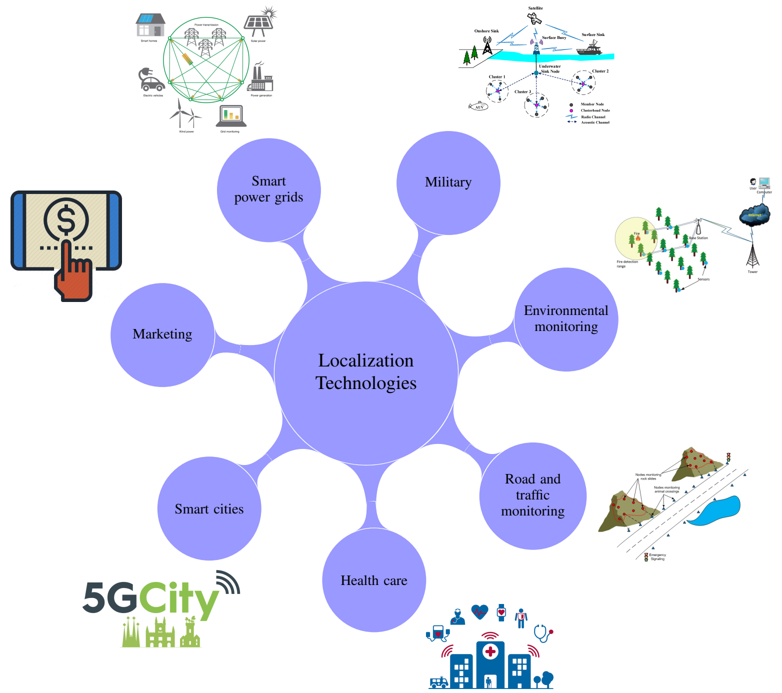

Fig. 1: A mind map of the most important applications of WSNs.

applications due to uncertainties in channel measurements, as well as noisy observations at the sensor nodes (SNs). In this work, we reconsider the proposed design in [19], in terms of signal fusion at the fusion center (FC) and power allocation at SNs, by taking into account the impact of channel estimation error, i.e., only imperfect CSI is available. We provide a closed form solution for optimal signal fusion and the optimal power allocation, which are obtained by solving convex optimization problem. We anticipate that our design will make the signal estimation much more robust to channel uncertainties, compared to the case that CSI estimation error is not taken into consideration.

In this paper, we study a wireless sensor network which is deployed to estimate multiple active target signals, where we consider only the imperfect CSI of both sensing and communication channels are known. In Section II, we model the operation of the sensors as well as FC of the wireless sensor network. In Section III, we propose an unbiased estimator where the variance of error can be further reduced by optimal power allocation to the sensor nodes and optimizing fusing weights at the FC. We formulate the optimal fusion rule problem in Section IV and optimal fusion weights are obtained by solving this problem. In Section V, we formulate a power allocation problem which is convex to minimize the total estimation error with transmit power constraints. The performance of the proposed estimator are analysed in Section VI. It is observed that a significant gain is obtained by taking imperfect CSI into consideration. The main results of this paper are summarized in Section VII.

Notations: The notation used throughout the paper is as follows: x denotes a scalar x while $\mathbf{x}$ is a vector $\mathbf{x}$ with entries x_i. $\mathbf{X}$ represents a matrix $\mathbf{X}$ with entries x_{ij}. x^*, $\mathbf{x}^*$ and $\mathbf{X}^*$ stand for the complex conjugate of scalar x and complex conjugate transpose of vector $\mathbf{x}$ and matrix $\mathbf{X}$, respectively. Also, $\mathbf{x}'$ and $\mathbf{X}'$ are the transpose of vector $\mathbf{x}$ and matrix $\mathbf{X}$, respectively. A diagonal matrix with diagonal entries $\mathbf{x}$ is written as $\mathbf{\Lambda}_{\mathbf{x}}$. $\mathcal{E}(\cdot)$ refers to the statistical expectation. The sets $\mathbb{N}$, $\mathbb{R}$ and $\mathbb{C}$ denote the set of all integer positive and non-zero numbers, the set of real numbers and the set of all complex numbers, respectively, while $\mathbb{C}^{m\times n}$ the set of all complex matrices of the size of $m \times n$. Finally, the Kronecker delta function is denoted as δ_{lm}.

II. System Model

In this section, we consider a wireless sensor network of K amplify-and-forward passive sensor nodes which can estimate the true values of L complex-valued active targets, i.e., $r_1, \ldots, r_L$ with the help of a fusion center (FC) as illustrated in Fig. 2. The index sets $\mathbb{F}_K = \{1, \ldots, K\}$ and $\mathbb{F}_L = \{1, \ldots, L\}$ correspond to the set of all sensors and targets, respectively. The target signals are sensed over wireless sensing channels by the sensor nodes. The sensors then transmits forward the observation of target signals to the FC using wireless communication channels. We assume all the channels (Sensing and communication channels) are frequency-flat and static during the observation process. We also assume that the target signals can be separately observed at each sensor. The power of each target is known, i.e., $R_l \coloneqq \mathcal{E}(|r_l|^2), l \in \mathbb{F}_L$, and the unknown true values of target signals remain constant over each estimation interval.

A. Imperfection in CSI

In this work, we consider that only imperfect channel state information of both sensing and communication channels are available. We define our channel error model similar to the one used in [18]. The true sensing channel $g_{lk} \in \mathbb{C}$ from target l to sensor k can be written as

$$g_{lk} = \tilde{g}_{lk} + \delta_{lk}^{(g)}, \quad k \in \mathbb{K}, \tag{1}$$

where $\tilde{g}_{lk}$ and $\delta_{lk}^{(g)}$ are the estimated CSI and estimation error for the sensing channel g_{lk}, respectively. The entries of sensing channel estimation error $\delta_{lk}^{(g)}$ is assumed to identically and independently distributed (iid) and zero-mean with the variance $\Delta_{lk}^{(g)}$. The expectation of the true sensing channel over the distribution of $\delta_{lk}^{(g)}$ can be stated as

$$\mathcal{E}\{|g_{lk}|^2\} = \mathcal{E}\{|\tilde{g}_{lk} + \delta_{lk}^{(g)}|^2\} = |\tilde{g}_{lk}|^2 + \Delta_{lk}^{(g)}, \tag{2}$$

where $\mathcal{E}\{.\}$ is the expectation operator. Similarly, the true communication channel $h_{lk} \in \mathbb{C}$ can be written as

$$h_{lk} = \tilde{h}_{lk} + \delta_{lk}^{(h)}, \quad k \in \mathbb{K}, \tag{3}$$

where $\tilde{h}_{lk}$ and $\delta_{lk}^{(h)}$ are the estimated channel coefficient and estimation error for the channel h_{lk}, respectively. The communication channel estimation error $\delta_{lk}^{(h)}$ is also assumed to be iid and zero-mean with the variance $\Delta_{lk}^{(h)}$. The expectation of the true communication channel over the distribution of $\delta_{lk}^{(h)}$ can be written as

$$\mathcal{E}\{|h_{lk}|^2\} = \mathcal{E}\{|\tilde{h}_{lk} + \delta_{lk}^{(h)}|^2\} = |\tilde{h}_{lk}|^2 + \Delta_{lk}^{(h)}. \tag{4}$$

B. Operation of SNs

When a target signal r_l is present, each sensor node k senses the target signal over the sensing channel g_{lk} which is contaminated by additive measurement noise $m_{lk} \in \mathbb{C}$. The noise is iid and zero-mean with the variance of M_{lk}. The noise is also independent from the target signals. We assume that over each estimation interval the sensing channel to remain unchanged. Therefore it can be treated as a time-invariant deterministic channel coefficient. Then, each SN amplifies its received target signal by the complex-valued coefficient $u_{lk},\ k \in \mathbb{F}_K$ and transmits it towards the FC. The transmitted signal from the sensor nodes can be stated as

$$x_{lk} = u_{lk}(m_{lk} + r_l\,(\tilde{g}_{lk} + \delta_{lk}^{(g)})),\ k \in \mathbb{F}_K. \tag{5}$$

Thus, the output power of sensor k for target l can be calculated as

$$X_{lk} \coloneqq \mathcal{E}\big(|x_{lk}|^2)\big) = |u_{lk}|^2\big(M_{lk} + R_l(|\tilde{g}_{lk}|^2 + \Delta_{lk}^{(g)})\big). \tag{6}$$

Furthermore, we assume that the power consumption of each sensor k is limited by power budget P_k, which results in the individual power constraint and can be represented as

$$\sum_{l \in \mathbb{F}_L} X_{lk} = \sum_{l \in \mathbb{F}_L} |u_{lk}|^2\big(M_{lk} + R_l(|\tilde{g}_{lk}|^2 + \Delta_{lk}^{(g)})\big) \leq P_k\,. \tag{7}$$

The total power consumption of the entire sensor network is also limited by a given sum-power P_{tot}, and can be stated as

$$\sum_{k \in \mathbb{F}_K} \sum_{l \in \mathbb{F}_L} X_{lk} \leq P_{\text{tot}}. \tag{8}$$

This power constraints allows to improve the life time of our network, since optimal power allocation is done for each estimation intervals.

C. Fusion Center

The transmitted signal from each sensor propagates through the communication channel $h_{lk} \in \mathbb{C}$ and arrives at the fusion center. We denote this signal by y_{lk} which can be expressed as

$$\begin{aligned} y_{lk} &\coloneqq n_{lk} + h_{lk}x_{lk} \\ &= n_{lk} + (\tilde{h}_{lk} + \delta_{lk}^{(h)})u_{lk}(m_{lk} + r_l\,(\tilde{g}_{lk} + \delta_{lk}^{(g)})), \end{aligned} \tag{9}$$

where n_{lk} is the additive noise at the fusion center antenna and is assumed to be zero-mean and iid with the variance N_{lk}. The communication channel h_{lk} is assumed to be static during the interval of estimation, and thus deterministic and time-invariant.

Since the system can make observations of each target separately, the fusion center multiplies the observation of r_l, done by all the sensors, with the fusion vector $\mathbf{v}_l \in \mathbb{C}^{K\times 1}$ which results into the observation values

$$\tilde{r}_l = \mathbf{v}_l'\mathbf{y}_l = \tilde{h}_l r_l + w_l\,, \tag{10}$$

where $\tilde{h}_l \coloneqq \mathbf{v}_l'\mathbf{c}_l$ is the effective observation channel and

$$[\mathbf{c}_l]_k \coloneqq \tilde{h}_{lk}u_{lk}\tilde{g}_{lk}\,. \tag{11}$$

Also

$$\begin{aligned} w_l \coloneqq \sum_{k \in \mathbb{F}_K} & v_{lk}n_{lk} + v_{lk}\delta_{lk}^{(h)}u_{lk}(m_{lk} + r_l\,(\tilde{g}_{lk} + \delta_{lk}^{(g)})) \\ & + v_{lk}\tilde{h}_{lk}u_{lk}(m_{lk} + r_l\,\delta_{lk}^{(g)}) \end{aligned} \tag{12}$$

is the effective noise.

III. Proposed Estimator

In this section, we propose an unbiased estimator whose variance of error can be further reduced by performing optimal power allocation and optimal fusion. If the power allocation and fusion strategy are chosen such that the effective channel $\tilde{h}_l$ in the observation (10) is always one, then the estimator

$$\hat{r}_l = \tilde{r}_l = r_l + w_l \tag{13}$$

is obviously unbiased. This is true since w_l is zero-mean as all the noise terms in equation (12) are zero-mean and independent. Such an unbiased estimator delivers the estimation error $\mathcal{E}(|w_l|^2)$ in estimating target r_l. The estimation error for target l, i.e., $f(\mathbf{u}_l, \mathbf{v}_l) \coloneqq \mathcal{E}(|w_l|^2)$ can be expressed as

$$\begin{aligned} f(\mathbf{u}_l,\mathbf{v}_l) &= \sum_{k\in\mathbb{K}} |v_{lk}|^2 N_{lk} + \sum_{k\in\mathbb{K}} |v_{lk}|^2|u_{lk}|^2 \left(|\tilde{h}_{lk}|^2 + \Delta_{lk}^{(h)}\right) M_{lk} \\ &\quad + R_l \sum_{k\in\mathbb{K}} |v_{lk}|^2|u_{lk}|^2 \left(\left(|\tilde{h}_{lk}|^2 + \Delta_{lk}^{(h)}\right)\Delta_{lk}^{(g)} + |\tilde{g}_{lk}|^2\Delta_{lk}^{(h)}\right), \\ &= \sum_{k\in\mathbb{K}} |v_{lk}|^2 N_{lk} + \sum_{k\in\mathbb{K}} |v_{lk}|^2|u_{lk}|^2 a_{lk}, \end{aligned} \tag{14}$$

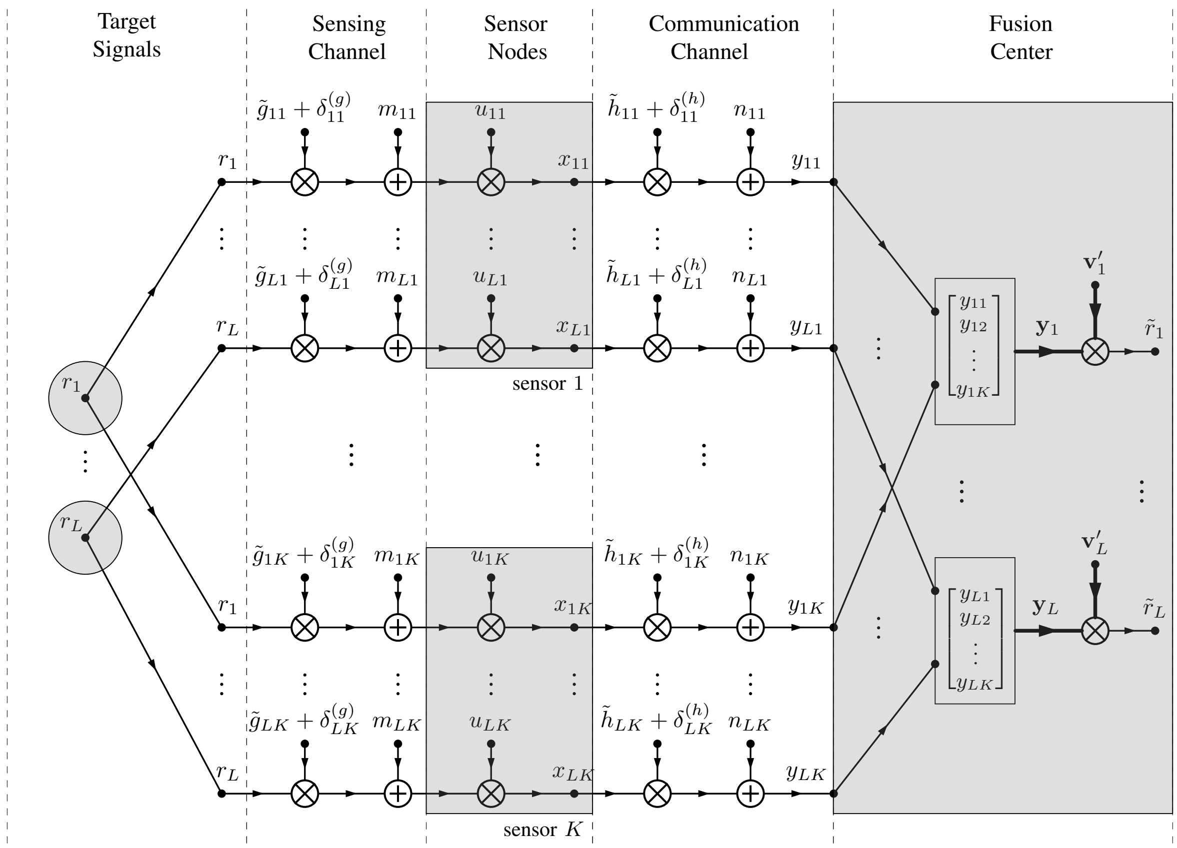

Fig. 2: Block diagram of the multi-target wireless sensor network. Targets are observed separately at each sensor node and fused separately at the fusion center.

where

$$a_{lk} := R_l \left(\left(|\tilde{h}_k|^2 + \Delta_k^{(h)} \right) \Delta_k^{(g)} + |\tilde{g}_k|^2 \Delta_k^{(h)} \right) + \left(|\tilde{h}_k|^2 + \Delta_k^{(h)} \right) M_k. \tag{15}$$

Note that, the targets signals are separately observed by the sensor nodes and separately forwarded to the FC. Therefore, the proposed optimization problem to minimize the total estimation error can be formulated as

$$\min_{\substack{\mathbf{u}_l \in \mathbb{C}^{K\times 1} \\ \mathbf{v}_l \in \mathbb{C}^{K\times 1} \\ l \in \mathbb{F}_L}} \sum_{l\in\mathbb{F}_L} \sum_{k\in\mathbb{F}_K} |v_{lk}|^2 (N_{lk} + |u_{lk}|^2 a_{lk}) \tag{16a}$$

$$\text{s.t.} \sum_{k\in\mathbb{F}_K} v_{lk} \tilde{h}_{lk} u_{lk} \tilde{g}_{lk} = 1, \forall l \in \mathbb{F}_L, \tag{16b}$$

$$\sum_{l\in\mathbb{F}_L} |u_{lk}|^2 (M_{lk} + R_l(|\tilde{g}_{lk}|^2 + \Delta_{lk}^{(g)})) \leq P_k, k \in \mathbb{F}_K, \tag{16c}$$

$$\sum_{k\in\mathbb{F}_K} \sum_{l\in\mathbb{F}_L} |u_{lk}|^2 (M_{lk} + R_l(|\tilde{g}_{lk}|^2 + \Delta_{lk}^{(g)})) \leq P_{\text{tot}}. \tag{16d}$$

The unbiasedness propoerty is guaranteed by the constraint (16b) which is obtained from (10) and (11). The individual and total power constraints are ensured by the constraints (16c) and (16d), resulting from equations (7) and (8).

IV. Optimizing Fusion Rule

Note that the fusion weights v_{lk} do not appear in the power constraints (7) and (8). Hence, the optimal fusion is the minimum of the objective (16a) subject to (16b). Also, the objective is the summation of the terms $f(\mathbf{u}_l, \mathbf{v}_l)$. Moreover, $\tilde{h}_l = 1$ depends only on $\mathbf{v}_l$ .i.e., the fusion weights for different targets are independent from one another. Consequently, the fusion problem breaks down into L independent optimizations. Therefore, the optimal fusion weights $\mathbf{v}_l^\star,\ l \in \mathbb{F}_L$ for target l is the optimal point of

$$f(\mathbf{u}_l, \mathbf{v}_l^\star) = \min_{\mathbf{v}_l \in \mathbb{C}^{K\times 1}} \mathbf{v}_l^* \mathbf{\Lambda}_{\mathbf{d}_l} \mathbf{v}_l \tag{17a}$$

$$\text{s.t.}\ \mathbf{v}_l' \mathbf{c}_l = 1\,. \tag{17b}$$

where

$$\mathbf{\Lambda}_{\mathbf{d}_l} = \text{diag}(\mathbf{d}_l), \tag{18}$$

$$[\mathbf{d}_l]_k := N_{lk} + |u_{lk}|^2 a_{lk}\,. \tag{19}$$

Similar to [19], using the Lagrange dual function of (17) and using the KKT conditions, the optimal fusion strategy $\mathbf{v}_l^\star$ and the error function $f(\mathbf{u}_l, \mathbf{v}_l^\star)$ for target $l \in \mathbb{F}_L$ can be derived as

$$\mathbf{v}_l^\star = \frac{\boldsymbol{\Lambda}_{\mathbf{d}_l}^{-1}(\mathbf{c}_l^*)'}{\mathbf{c}_l^*\boldsymbol{\Lambda}_{\mathbf{d}_l}^{-1}\mathbf{c}_l}\,, \tag{20a}$$

$$f(\mathbf{u}_l, \mathbf{v}_l^\star) = \frac{1}{\mathbf{c}_l^*\boldsymbol{\Lambda}_{\mathbf{d}_l}^{-1}\mathbf{c}_l}\,. \tag{20b}$$

Using (11) and (18), we can rewrite $f(\mathbf{u}_l, \mathbf{v}_l^\star)$ as

$$f(\mathbf{u}_l, \mathbf{v}_l^\star) = \frac{1}{\sum\limits_{k\in\mathbb{F}_K} \frac{|\tilde{h}_{lk}|^2|u_{lk}|^2|\tilde{g}_{lk}|^2}{N_{lk}+|u_{lk}|^2 a_{lk}}}\,. \tag{21}$$

V. Power Allocation

As it can be noticed that the power constraints (16c) and (16d) are independent from the choice of fusion weights. In order to minimize the total estimation error further, we need to perform optimal power allocation as the error function $f(\mathbf{u}_l, \mathbf{v}_l^\star)$ still depends on power allocation. Let us define

$$\alpha_{lk}^2 := \frac{|\tilde{h}_{lk}|^2|\tilde{g}_{lk}|^2}{a_{lk}}\,, \beta_{lk}^2 := \frac{N_{lk}\big(M_{lk} + R_l(|\tilde{g}_{lk}|^2 + \Delta_{lk}^{(g)})\big)}{a_{lk}}\,. \tag{22}$$

Then, by replacing (6) into (21) the estimation error of target l can be stated as a function of X_{lk}:

$$f(\mathbf{u}_l, \mathbf{v}_l^\star) = \frac{1}{\sum\limits_{k\in\mathbb{F}_K} \frac{\alpha_{lk}^2 X_{lk}}{X_{lk}+\beta_{lk}^2}}\,. \tag{23}$$

Thus, the total estimation error (16a) can be formulated as

$$\sum_{l\in\mathbb{F}_L} f(\mathbf{u}_l, \mathbf{v}_l^\star) = \sum_{l\in\mathbb{F}_L} \frac{1}{\sum\limits_{k\in\mathbb{F}_K} \frac{\alpha_{lk}^2 X_{lk}}{X_{lk}+\beta_{lk}^2}}\,. \tag{24}$$

Furthermore, the resulting power allocation problem can be stated as

$$\min_{\substack{X_{lk}\in\mathbb{R}\\ l\in\mathbb{F}_L, k\in\mathbb{F}_K}} \sum_{l\in\mathbb{F}_L} \frac{1}{\sum\limits_{k\in\mathbb{F}_K} \frac{\alpha_{lk}^2 X_{lk}}{X_{lk}+\beta_{lk}^2}} \tag{25a}$$

$$\text{s.t.} \quad X_{lk} \geq 0\,,\ l\in\mathbb{F}_L\,,\ k\in\mathbb{F}_K\,, \tag{25b}$$

$$\sum_{l\in\mathbb{F}_L} X_{lk} \leq P_k\,,\ k\in\mathbb{F}_K\,, \tag{25c}$$

$$\sum_{k\in\mathbb{F}_K}\sum_{l\in\mathbb{F}_L} X_{lk} \leq P_{\text{tot}}\,. \tag{25d}$$

The above problem (25) is similar to the power allocation problem in [19] which is convex. The problem (25) is convex for its objective function and its feasible set is also convex. Since the resulting optimization problem is convex, we can easily solve the problem for global optimum using any convex solver.

VI. Simulations

By using numerical simulations, we analyse the performance of the proposed estimator for a wireless network with $K = 20$ SNs to estimate multiple active targets. We consider all the estimated sensing and communication channels and their corresponding estimation errors are zero-mean and follow a Gaussian distribution with the variances ${\sigma_g}^2$, ${\sigma_h}^2$, Δ_g , and Δ_h, respectively. Default network parameters values used for our simulations are given in the Table I. For each set of both sensing and communication channel realizations, i.e., g_k, h_k, 10000 realizations of r, n_k and m_k are generated to evaluate the network performance. Then, the results are averaged over 1000 channel realizations. The curves *'Robust'* represents the proposed robust algorithm, where only the imperfect

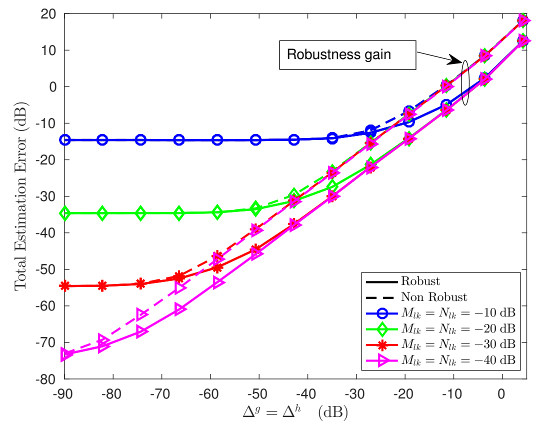

Fig. 3: Total estimation error (dB) versus Channel estimation error (dB) for different noise power.

CSI is known and statisical properties of the estimation is taken into consideration. The curves *'Non-Robust'* represents non-robust algorithm, where the statistics of the channel estimation error is not taken into consideration.

In Fig 3, the performance of the network in terms of total estimation error is plotted with respect to the variance of the estimation error, $\Delta_g = \Delta_h$, on the sensing and communication channels for different noise levels at the SNs and FC. It is assumed that the variance of channel estimation error is same for all the sensor nodes. The WSN is used to estimate $L = 4$ active target signals. It can be clearly observed that the resulting total estimation error increases as the variance of the channel estimation error increases or as the noise power increases. We also notice that the robust algorithm outperforms the non-robust algorithm in all the noise and estimation error values. The performance gain increases as $\Delta_g = \Delta_h$ increases and also for small values of noise power.

In Fig 4, the resulting network performance is depicted in terms of total estimation error with respect to target signal power R_l for different number of targets. We can see that the resulting total estimation error increases as the target signal power increases. As expected, increase in the number of targets results in higher estimation error. It can be clearly noticed that the robust algorithm performs better for higher values of signal power,or equivalently for high signal to noise ratio regime.

In Fig 5, the impact of number of target signal L on the performance of the network is analysed. Here, the resulting total estimation error increases as the number of active targets increases. We can also notice that the performance of the robust algorithm is better for higher number of targets.

R_l	${\sigma_g}^2$	${\sigma_h}^2$	Δ_g	Δ_h	N_{lk}	M_{lk}	P_k	P_{tot}
10	1	1	0.1	0.1	0.1	0.1	1	5

TABLE I: Reference parameters

VII. Conclusion

In this paper, we study a multi-target wireless sensor network for estimating true values of target signals, where only the imperfect CSI is known. It is assumed that the targets signals are observed separately, i.e., observed due to either orthogonality in frequency or difference in their physical nature. We have proposed an unbiased estimator which minimizes estimation error under sensor transmit power constraints. This is attained by optimizing the power allocation among sensor nodes as well as optimizing the data fusion (fusion

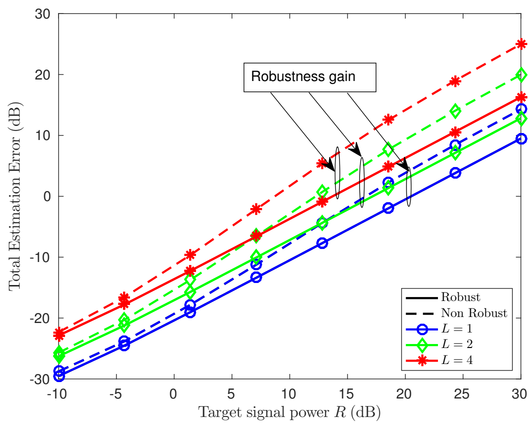

Fig. 4: Total estimation error (dB) versus Target signal power (dB) for different number of target signals.

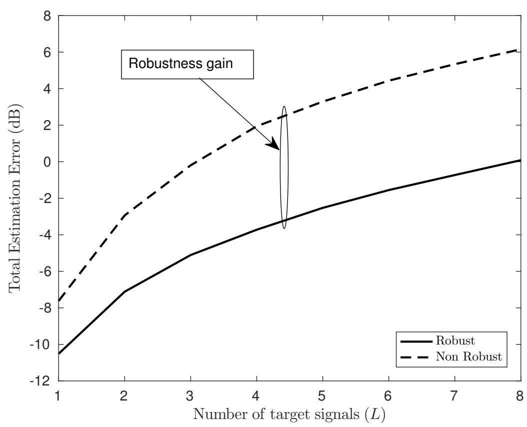

Fig. 5: Total estimation error (dB) versus Number of target signals.

weights) at the FC. Using numerical simulations, we analyse the behaviour of the sensor network for different network parameters. It can be observed that the proposed robust algorithm outperforms the non-robust algorithm where the statistical properties of the channel estimation error are neglected.

REFERENCES

[1] M. Kocakulak and I. Butun, "An overview of wireless sensor networks towards internet of things," in *2017 IEEE 7th Annual Computing and Communication Workshop and Conference (CCWC)*, Jan 2017, pp. 1–6.

[2] "What is MEMS technology?" https://www.memsnet.org/about/what-is.html.

[3] M. Arik and O. B. Akan, "Collaborative mobile target imaging in uwb wireless radar sensor networks," *IEEE Journal on Selected Areas in Communications*, vol. 28, no. 6, pp. 950–961, Aug 2010.

[4] W. Wang, "Distributed passive radar sensor networks with near-space vehicle-borne receivers," *IET Wireless Sensor Systems*, vol. 2, no. 3, pp. 183–190, September 2012.

[5] P. Antonio, F. Grimaccia, and M. Mussetta, "Architecture and methods for innovative heterogeneous wireless sensor network applications," *Remote Sensing*, vol. 4, no. 5, pp. 1146–1161, 2012.

[6] R. Abbasi, "Icecube neutrino observatory," *International Journal of Modern Physics D*, vol. 19, no. 06, pp. 1041–1048, 2010.

[7] L. Changchang, X. Hao, H. Xuezhi, and C. Weidong, "The distributed passive radar 3-D imaging and analysis in wavenumber domain," in *Signal Processing (ICSP), 2010 IEEE 10th International Conference on*. IEEE, 2010, pp. 2051–2054.

[8] G. Alirezaei, O. Taghizadeh, and R. Mathar, "Optimum power allocation with sensitivity analysis for passive radar applications," *IEEE Sensors Journal*, vol. 14, no. 11, pp. 3800–3809, Nov. 2014.

[9] G. Alirezaei, M. Reyer, and R. Mathar, "Optimum power allocation in sensor networks for passive radar applications," *IEEE Transactions on Wireless Communications*, vol. 13, no. 6, pp. 3222–3231, Jun. 2014.

[10] H. Godrich, A. P. Petropulu, and H. V. Poor, "Power allocation strategies for target localization in distributed multiple-radar architectures," *Signal Processing, IEEE Transactions on*, vol. 59, no. 7, pp. 3226–3240, 2011.

[11] M. Cardei, M. T. Thai, Y. Li, and W. Wu, "Energy-efficient target coverage in wireless sensor networks," in *Proceedings IEEE 24th Annual Joint Conference of the IEEE Computer and Communications Societies.*, vol. 3, March 2005, pp. 1976–1984.

[12] W. L. Yeow, C. K. Tham, and W. C. Wong, "Energy efficient multiple target tracking in wireless sensor networks," *IEEE Transactions on Vehicular Technology*, vol. 56, no. 2, pp. 918–928, March 2007.

[13] J. Liu, M. Chu, and J. E. Reich, "Multitarget tracking in distributed sensor networks," *IEEE Signal Processing Magazine*, vol. 24, no. 3, pp. 36–46, May 2007.

[14] W. Li and W. Zhang, "Multiple target localization in wireless visual sensor networks," *Frontiers of Computer Science*, vol. 7, no. 4, pp. 496–504, 2013.

[15] K. Xin, P. Cheng, and J. Chen, "Multi-target localization in wireless sensor networks: a compressive sampling-based approach," *Wireless Communications and Mobile Computing*, vol. 15, no. 5, pp. 801–811, 2015.

[16] H. Dai, Z.-M. Zhu, and X.-F. Gu, "Multi-target indoor localization and tracking on video monitoring system in a wireless sensor network," *Journal of Network and Computer Applications*, vol. 36, no. 1, pp. 228–234, 2013.

[17] L. Yang, J. Liang, and W. Liu, "Radar sensor (rs) deployment for multi-target detection," in *Wireless Communications and Signal Processing (WCSP), 2014 Sixth International Conference on*. IEEE, 2014, pp. 1–5.

[18] V. Radhakrishnan, O. Taghizadeh, and R. Mathar, "Distributed estimation and power allocation for passive radar sensor networks with imperfect CSI," in *22nd International ITG Workshop on Smart Antennas (WSA 2018)*, Bochum, Germany, Mar. 2018, pp. 1–5. [Online]. Available: http://www.ti.rwth-aachen.de/publications/output.php?id=1116&table=proceeding&type=pdf

[19] E. Zandi, P. M. Vieting, O. Taghizadeh, and R. Mathar, "Power allocation for orthogonally-observed multi-target sensor networks," in *2017 IEEE International Conference on Wireless for Space and Extreme Environments (WiSEE'17)*, Montreal, Canada, Oct. 2017. [Online]. Available: http://www.ti.rwth-aachen.de/publications/output.php?id=1098&table=proceeding&type=pdf