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In accordance with the requirements for the degree of Doctor of Philosophy

June 6, 2017
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1. Introduction

Motivation

- WSNs spatially deployed over a field can be designed to collect information and monitor many phenomena of interest.
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- Important role in several daily application scenarios such as health-care monitoring, home applications, smart farming, environment monitoring, and military.

Figure 1. (left) A WSN architecture. (right) Smart city infrastructure.
1. Introduction

**Motivation**

- WSNs spatially deployed over a field can be designed to collect information and monitor many phenomena of interest.
- Important role in several daily application scenarios such as health-care monitoring, home applications, smart farming, environment monitoring, and military.

**Figure 1:** (left) A WSN architecture. (right) Smart city infrastructure.
Low Power Hardware: Clearly, the biggest design constraint in WSNs still remains the power consumption. Even-though the SNs are being designed using low-power micro controllers, their power dissipation is still orders of magnitude too high.
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Design Challenges in WSNs

- **Low Power Hardware:** Clearly, the biggest design constraint in WSNs still remains the power consumption. Even-though the SNs are being designed using low-power micro controllers, their power dissipation is still orders of magnitude too high.

- **Resource Constraints:** Battery operated devices with limited on-board energy, both the system lifetime and communication bandwidth (BW) are restricted. Both the signal processing and communication should be carefully designed to consume minimal energy in order to extend the lifetime and improve the overall reliability of the WSN.
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Design Challenges in WSNs

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- **Network Security:** Usually unattended (geographically dispersed) and this makes them vulnerable to attacks. The overall detection and estimation strongly depends on the reliability of these SNs.


Contribution-Publications List


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2. Optimal Quantization and Power Allocation

System Architecture

Figure 2: Communication architecture between peripheral SNs and the FC. Each SN generates a test statistic by observing the target and can communicate with the FC only over an energy-constrained/bandwidth-constrained link.
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Figure 3: Equal weight \( (\alpha_i = \frac{1}{\sqrt{M}}, \forall i) \) and optimal weight combining \( (\alpha = \alpha_{opt}) \) transmit power and channel quantization bits allocation for \( P_{fa} = 0.1, P_t = 10, U = 0.1, \) and \( M = 10 \).
2. Simulation Results

Figure 4: Receiver operating characteristic with $P_t = 10$, $U = 0.1$ and $M = 10$ for two different weighting schemes.
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Figure 5: Probability of detection ($P_d$) versus the signal to noise ratio ($\xi_a$) for $M = 20$, $N = 10$, $P_t = 10$, $P_{fa} = 0.1$ and $B = 0.5$. 

- Opt LRT-based
- LRT-based in (4.4.8)
- Opt lin comb in (4.4.9)
- Eq LRT-based
- Linear combi in (4.3.9)
- Eq lin combining
Figure 6: Probability of detection ($P_d$) versus the number of samples ($N$) for $M = 10$ sensors, $P_{fa} = 0.1$, $\xi_a = -8.5$ dB and $B = 1$. 

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Figure 7: Probability of detection ($P_d$) versus number of sensors ($M$) for $N = 10$, $P_t = 10$, $P_{fa} = 0.1$, $\xi_a = -8.5$ dB and $B = 0.5$. 

Optimum fusion rule LRT-based
LRT-based with weights in (4.4.8)
Optimum linear combining in (4.4.9)
Equal weight LRT-based
Linear combining with weights in (4.3.9)
Equal weight linear combining
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**Communication Architecture**

![Diagram of a distributed communication architecture among peripheral SNs. The SNs have partial connectivity (thin lines) among themselves (i.e., not a complete graph).](image)

**Figure 8:** A distributed communication architecture among peripheral SNs. The SNs have partial connectivity (thin lines) among themselves (i.e., not a complete graph).
4. Quantized Distributed Soft Decision Fusion Rule

Proposition

- Here we propose a scheme, where SN $i$ encodes the data (using a simple uniform quantizer with $q_i$ bits) prior to information exchange.

$\Upsilon$ is a SNR threshold parameter and $\text{SNR}_{ij}$ defined as:

$$\text{SNR}_{ij} = \frac{p_{t,ij} h_{ij}^2 \zeta_0 d_{ij}}{\gamma_{ij}}.$$
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- Here we propose a scheme, where SN $i$ encodes the data (using a simple uniform quantizer with $q_i$ bits) prior to information exchange.

- We also propose to establish a link between any two SNs $i$ and $j$ based on the (known) SNR at node $j$, i.e.

\[
\begin{align*}
\text{if } SNR_{ij} < \Upsilon, & \quad e_{ij} = e_{ji} = 0 \\
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- We propose to quantize with $q_i$ bits at SN $i$ before transmitting to SN $j$:

$$q_i \leq \frac{1}{2} \log_2 (1 + \Upsilon) \text{ bits/sample}$$

A large $\Upsilon$ means:
1. Fewer communication links and so slower information diffusion across the network.
2. An increase in the number of bits that each SN can transmit to its neighbors.

A small $\Upsilon$ means:
1. Establishes a more connected graph and dictates a faster information diffusion across the network.
2. Allows less transmission bits resulting in an increase in the quantization noise variance.
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Figure 9: Normalized average power consumption ($\mathbb{E}[P_T]$), achievable probability of detection ($P_d^*$) and the average communication link density ($\rho$) versus $\gamma$, with $\sigma_{eh}^2 = 0$, decision fusion in (5.4.16), $P_{fa}^g = 0.1$, $U = 3$, $N = 20$, $M = 17$ and with $\alpha_i$ (scaled by $M$).
Figure 10: Averaged (over 500 $h_{ij}$ realizations) ROC for the proposed two-step weighted algorithm with decision fusion in (40), $U = 3$, $N = 20$, $M = 17$, $K_2 = 3$, $\Upsilon = 30$, $\sigma_{e_h}^2 = 0$ and with $\alpha_i$ (scaled by $M$) in (5.3.9).
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Figure 11: Averaged (over 500 $h^2_{ij}$ realizations) ROC against first step iterations number ($K_1$), with decision fusion in (41), $K_2 = 2$, $U = 3$, $N = 20$, $M = 17$, $\Upsilon = 10$, $\sigma^2_{e_h} = 0$ and with $\alpha_i$ (scaled by $M$) in (5.3.9).
Figure 12: Averaged (over 500 $h_{ij}^2$ realizations) probability of detection ($P_g^f$) against the signal to noise ratio ($\xi_a$) with $P_g^f = 0.1$, $U = 3$, $N = 20$, $M = 17$, $K_1 = 320$, $\gamma = 20$, $\xi_i = \xi$, $\forall i$ in (4) and with $\alpha_i$ (scaled by $M$) in (5.3.9): (left) ideal, $\sigma_{eh}^2 = 0$; (right) non-ideal, $\sigma_{eh}^2 \neq 0$. 

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Figure 13: Averaged (over 500 $h_{ij}^2$ realizations) ROC for the proposed (quantized) two-step weighted fusion rule with $U = 3$, $N = 20$, $\Upsilon = 20$, $M = 17$ and with $\alpha_i$ (scaled by $M$) in (5.3.9).

- Proposed weighted two-step with (5.4.15)
- Unquantized eq. comb. ($\alpha_i = 1$) in (5.3.14)
- Proposed eq. comb. ($\alpha_i = 1$) two-step with (5.4.16)
- Proposed eq. comb. ($\alpha_i = 1$) two-step with (5.4.15)
- Proposed weighted two-step with (5.4.16)
- Centr. opt. linear rule (5.3.12)
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![Graph showing probability of detection vs signal to noise ratio](image)

**Figure 14:** Probability of detection \( (P_{d}^{g}) \) versus the signal to noise ratio \( (\xi_{a}) \) for \( M = 13, \Upsilon = 72, U = 2, N = 20, P_{fa}^{g} = 0.1 \) and \( \xi_{i} = \xi, \forall i \) in (3.2.4) and \( \alpha_{i} = 1, \forall i \) in (5.4.4). The topology used is given in right of Fig. 5.5.
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5. Sensor Detection in the Presence of Falsified Observations

**Motivation**

Geographically dispersed to cover large areas, the SNs are constrained in both bandwidth and power. Usually unattended and this makes them vulnerable to different attacks.

**Contributions**

- The problem of centralized detection in the presence of compromised SNs is investigated.
- Attacker-based and FC-based parameter optimization are considered and some expressions have been derived.
- A reputation based scheme to identify the compromised SNs in the network and control their influence to the global FC decision is also proposed.
5. Sensor Detection in the Presence of Falsified Observations

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1. Geographically dispersed to cover large areas, the SNs are constrained in both bandwidth and power. Usually unattended and this makes them vulnerable to different attacks.

2. The overall detection performance strongly depends on the reliability of these SNs in the network.

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3. While fusing the data received by the spatially deployed SNs allows the FC to make a reliable decision, it is possible that one or more SNs (compromised by an attacker) deliberately falsify their local observations.

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Communication Architecture

Figure 15: Under attack communication architecture between peripheral SNs and the FC. While the honest SNs test statistics remain unchanged, the compromised SNs falsify their test statistics before transmitting to the FC.
Figure 16: SN optimal transmit power ($p_{i}^{o}$) and channel bit allocation ($L_{i}$) with $P_t = 60$, $U = 3$, $\xi_a = -10.5$ dB, $N = 20$, $\beta = 0.1$ and $\sigma^2_{e_h} = 0$. 

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Figure 17: Probability of detection ($P_d$) versus probability of false alarm ($P_{fa}$) with $U = 3$, $P_t = 60$, $M = 12$, $N = 20$, $C_i = 0.9$, $\forall i$ and $\sigma_{eh}^2 = 0$.
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Figure 18: Probability of detection ($P_d$) versus probability of false alarm ($P_{fa}$), with $U = 3$, $\xi_a = -10.5$ dB, $P_t = 60$, $M = 12$, $N = 20$, $\beta = 0.2$, $\sigma^2_{eh} = 0$ and with optimum weights in (6.2.22).
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Figure 19: Modified deflection coefficient ($\tilde{d}^2$) versus the attacker strength ($C$) with $U = 3$, $\xi_a = -10$ dB, $s_i = 0.1$, $P_t = 60$, $M = 12$, $N = 20$, $\beta = 0.1$ and $\sigma_{eh}^2 = 0$. 

$\tilde{d}^2$ modified deflection coefficient, $\tilde{d}^2$ is the function of $C$, $U$, $s_i$, $P_t$, $M$, $N$, $\beta$, and $\sigma_{eh}^2$. The optimal and non-optimal cases are shown in the graph.
5. A Secure Sub-optimum Detection Scheme in Under-Attack WSNs

Figure 20: Under attack schematic communication architecture between peripheral SNs and the fusion center (FC). While the $i^{th}$ ($i = \{1, 2, 4, 6\}$) honest SN indicator (test statistic) remains unchanged (i.e., $\tilde{I}_i = I_i$), the $j^{th}$ ($j = \{3, 5\}$) compromised SN falsify its indicator (test statistic) as in (6.3.7) before transmitting to the FC.
5. A Secure Sub-optimum Detection Scheme in Under-Attack WSNs

**FC Optimum Weighting**

\[
\alpha^i_{opt} = \frac{(1 - \beta) (p^i_d - p^i_{fa}) + \beta (p^i_{fa} - p^i_d) (2P^{fa}_C - 1)}{(1-\beta) (p^i_d (1-p^i_d)) + \beta (P^{flip}_C + p^i_{fa} (1-2P^{flip}_C))(1-P^{flip}_C + p^i_{fa} (2P^{flip}_C - 1))}. \tag{1}
\]

Depends upon the local \(p^i_{fa}\) and the \(p^i_d\) as well as on the \(\beta\) (fraction of compromised SNs) and the probability of flipping the local decisions by the attacker. The FC cannot implement the optimum weight combining fusion rule.

**Attacker Flipping Probability Optimisation**

Lemma 6.3.2: The optimum flipping probability \(P^{flip}_{C, opt}\) which minimizes the modified deflection coefficient is:

\[
P^{flip}_{C, opt} = \beta - 1 \left( \frac{\sum_{i=1}^{M} \alpha_i (p^i_d - p^i_{fa})}{\sum_{i=1}^{M} \alpha_i (p^i_{fa} - p^i_d)} \right) + \frac{1}{2} \tag{2}
\]
5. Simulation Results 1/6

Figure 21: The reliability metric \( r_i \) versus the FC detection threshold \( \Lambda_f \) against the SNs with \( M = 40, N = 20, \beta = 0.5, P_{\text{flip}}^C = 1 \) and \( K = 150 \).
Figure 22: Probability that the (compromised) SN 37 has been truly detected ($P_{d, true}^{37}$) versus the FC detection threshold ($\Lambda_f$) with $M = 40$, $N = 20$, $\beta = 0.5$, $P_{flip}^C = 1$ and $\delta = 0.009$. 
5. Simulation Results 3/6

**Figure 23:** Average compromised SNs detection probability and honest SNs mis-detection probability versus the time window length ($K$) and against $\beta$ with $M = 40$, $N = 20$, $P_{C}^{flip} = 1$ and $\delta = 0.009$. 

$P_{true}^{d}$, $\Lambda_f = 5$

$P_{false}^{d}$, $\Lambda_f = 5$

$P_{true}^{d}$, $\Lambda_f = 13$

$P_{false}^{d}$, $\Lambda_f = 13$
Figure 24: The $P_d - P_{fa}$ metric versus the time window length ($K$) against the FC detection threshold ($\Lambda_f$) with $M = 40$, $N = 20$, $\beta = 0.25$, $P_{C_{flip}} = 0.2$, $\delta = 0.95$ and $\mu = 10$. 

5. Simulation Results 4/6
Figure 25: Probability of detection ($P_d$) versus probability of false alarm ($P_fa$) with $M = 40$, $N = 20$, $\beta = 0.5$, $P_{flip}^C = 1$ and $K = 5$. 

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Figure 26: Probability of detection ($P_d$) versus probability of false alarm ($P_{fa}$) against $\delta$ and $\mu$ with $M = 40$, $N = 20$, $\beta = 0.25$, and $P_{flip}^C = 1$. 

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Summary

- We derive the optimum fusion rule and then analyze sub-optimum fusion rules that are realizable and easily implemented in practical WSN deployment scenarios. The effect of fading channels on detection performance is minimized by solving the resource allocation problem.
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- We derive the **optimum fusion** rule and then analyze **sub-optimum fusion** rules that are realizable and easily implemented in practical WSN deployment scenarios. The effect of fading channels on detection performance is minimized by solving the **resource allocation** problem.

- A two-step consensus-based approach with weight combining quantized test statistics exchange is proposed. We relate the communication topology with the number of bits to be shared among SNs. It turns out that there is an **optimum topology** that maximizes the detection performance.

Centralized detection in the presence of compromised SNs is also investigated. Attacker and FC based parameter optimization are considered and some expressions have been derived. A reputation based scheme to identify the compromised SNs in the network and control their influence to the global FC decision is also proposed.
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- Centralized detection in the presence of **compromised** SNs is also investigated. Attacker and FC based parameter optimization are considered and some expressions have been derived. A reputation based scheme to **identify** the compromised SNs in the network and control their influence to the global FC decision is also proposed.
Key Conclusions

- Shown that spatially distributed SNs across the field can offer a **reliable** operation for event **detection** applications. The system detection performance and the WSN’s operating **lifetime** can be further improved by means of resource allocations, optimisation and signal processing algorithms.
Key Conclusions

- Shown that spatially distributed SNs across the field can offer a reliable operation for event detection applications. The system detection performance and the WSN’s operating lifetime can be further improved by means of resource allocations, optimisation and signal processing algorithms → complexity to be kept as simple as possible.

- Derive sub-optimum but simple fusion rules (requiring simple hardware) that offer reliable and good detection performance.

- A better but more complex approach is to possibly identify these compromised SNs and control their influence on the FC decision → Offers an improved detection performance but requires observing the SN’s local reports for a period of time. A larger observation time period (K) may lead to a large detection delay that is critical for most of the event detection applications.

- We have addressed the fully distributed detection problem and proposed signal processing algorithms for such an approach → Very attractive from both the signal processing perspective and the communication point of view.
Key Conclusions

- Shown that spatially distributed SNs across the field can offer a reliable operation for event detection applications. The system detection performance and the WSN’s operating lifetime can be further improved by means of resource allocations, optimisation and signal processing algorithms. Complexity to be kept as simple as possible.

- The data fusion problem: we derive the optimal fusion rules (i.e., for attack-free and under-attack WSN scenarios) and have shown that these fusion rules are not implementable in practice and require complex local signal processing.

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- A better but more complex approach is to possibly identify these compromised SNs and control their influence on the FC decision $\Rightarrow$ Offers an improved detection performance but requires observing the SN’s local reports for a period of time. A larger observation time period (K) may lead to a large detection delay that is critical for most of the event detection applications.

- We have addressed the fully distributed detection problem and proposed signal processing algorithms for such an approach.
Key Conclusions

- Shown that spatially distributed SNs across the field can offer a reliable operation for event detection applications. The system detection performance and the WSN’s operating lifetime can be further improved by means of resource allocations, optimisation and signal processing algorithms complexity to be kept as simple as possible.

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- We have addressed the fully distributed detection problem and proposed signal processing algorithms for such an approach Very attractive from both the signal processing perspective and the communication point of view.