Multisensor Data Fusion for Water Quality Monitoring Using Wireless Sensor Networks

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***Abstract*—In this paper, the application of hierarchical wireless sensor networks in water quality monitoring is investigated. Adopting a hierarchical structure, the set of sensors is divided into multiple clusters where the value of the sensing parameter is almost constant in each cluster. The members of each cluster transmit their sensing information to the local fusion center (LFC) of their corresponding cluster, where using some fusion rule, the received information is combined, and then possibly sent to a higher-level central fusion center (CFC). A two-phase processing scheme is also envisioned, in which the first phase is dedicated to detection in the LFC, and the second phase is dedicated to estimation in both the LFC and the CFC. The focus of the present paper is on the problem of decision fusion at the LFC: we propose hard- and soft-decision maximum a posteriori (MAP) algorithms, which exhibit flexibility in minimizing the total cost imposed by incorrect detections in the first phase. The proposed algorithms are simulated and compared with conventional fusion techniques. It is shown that the proposed techniques result in lower cost. Furthermore, when the number of sensors or the amount of contamination increases, the performance gap between the proposed algorithms and the existing methods also widens.**

***Index Terms*—water quality monitoring, contamination warning systems, wireless sensor networks, data fusion, distributed detection, maximum a posteriori algorithms.**

I. Introduction

Providing a reliable supply of potable water is an important goal in today's society. To this end, water contamination warning systems (WCWSs) are typically deployed to monitor the quality of water. At the same time, wireless sensor networks (WSNs) have found extensive applications in monitoring physical or environmental conditions such as temperature, sound, pressure, etc. Therefore in this context, WCWSs have been one of the most recent embodiments of WSNs [1]–[4].

In a WCWS, the type of the parameters that must be monitored and controlled depends on the use of water. Specifically, for drinking water, chemical contaminations are more important, while for industrial applications, physical contaminations are more relevant, because these physical objects may damage industrial equipments that work with water [5].

Being physical devices, sensors used in practice are typically plagued with a wide range of non-ideal characteristics. For instance, the variance of the sensing error increases with the age of the sensor [6]. Therefore, when used in isolation, a particular sensor may produce large sensing errors, responsible for incorrect or missing alarms. On the other hand, reliable and high-quality sensors, with lower variance in the sensing error, are invariably more expensive. As such, in a WCWS where many sensors may be needed to provide sufficient coverage of large geographical areas, e.g., a river or a water distribution system, the total cost may prove economically infeasible.

In addition, for a WSN, sensing error is not the only source of error: the quality of the wireless links is another major limiting factor. Therefore, to combat both sources of error, collaboration among the sensors in the network is useful in enabling distributed parameter estimation (DPE) [3]. In DPE, each sensor is allowed to either send its measurement to a fusion center, or share it with other sensors which are in its transmission range [7].

The hierarchical structure increases the efficiency of the WSN in many aspects. The monitoring area is divided into multiple clusters, where the value of the sensing parameter is almost constant inside each cluster, but may vary from one cluster to another. In general, the cross correlation between the values of a parameter in two clusters depends on some factors, such as relative distance between the clusters, direction and velocity of the water flow. As shown in Fig. 1, each cluster has a local fusion center (LFC), which makes a local decision, and in turn sends it to a central fusion center (CFC) for the final decision. When a WSN is used to monitor the water quality, the measurements from different types of sensors, e.g., pH, DO (dissolved oxygen), arsenic, permanganate, etc., may be acquired and transmitted to the LFC [3]. Using the hierarchical structure not only reduces the required power for communication between sensors (thus increasing the lifetime of the batteries), but also reduces the complexity of routing and scheduling in the network. In particular, the cluster size can be optimized to minimize the required communications overhead among sensors [8].

To increase the bandwidth efficiency in a DPE-based system, a two-phase processing scheme is envisioned. In the first phase, the water quality is constantly monitored: each sensor periodically sends a binary signal to the LFC, where bit 1 signifies that the water is contaminated, and bit 0 means the water quality is acceptable. Using a specified fusion rule (to be described later), the LFC combines the received binary

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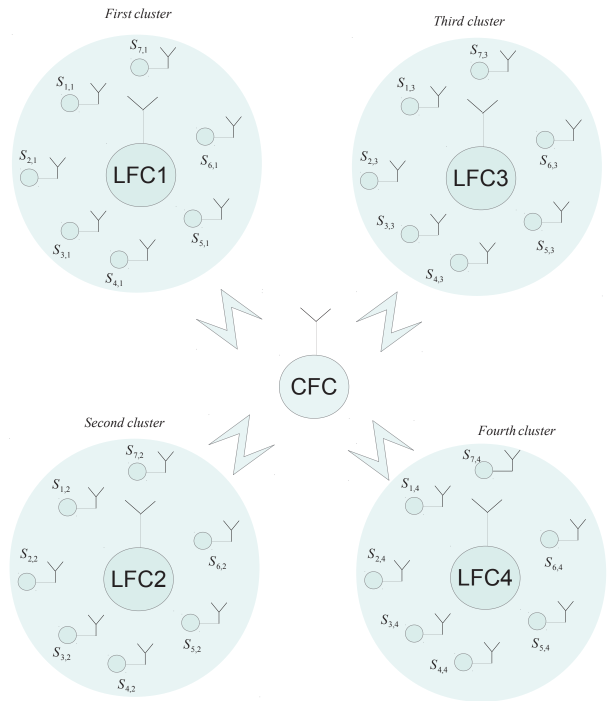

Fig. 1. Distributed parameter estimation using a hierarchical WSN.

signals to make a decision. If contamination is detected, the second phase is invoked: the LFC dedicates a much larger bandwidth to its sensors, and queries them to send the actual values of the measurements for more exact processing, to be forwarded to the CFC. This two-phase approach reduces the required bandwidth, because the system should operate mostly in the first phase, where only low-rate binary decisions are transmitted from sensors to the LFC. This paper focuses on the local detection in the LFC, i.e., distributed detection in phase 1, while deferring phase 2 to a future work.

The objective is to formulate an optimum detection rule for each LFC. Conventional fusion techniques for binary decisions are OR-rule, AND-rule, and n-out-of-M-rule. For the simpler OR-rule and AND-rule, the received binary decisions from the sensors are simply fed into a logical OR or AND operator to make the final decision. However, with the more general n-out-of-M-rule, the final decision is a logical true, i.e., bit 1, if at least n out of M sensors have triggered alarm. Obviously the AND-rule results in a high rate of missed detections, making it unsuitable in WCWS where any contamination misdetection might be dangerous. On the other hand, the OR-rule leads to a high false alarm rate, so that the system may operate mostly in the second phase, where bandwidth and the other network resources are wasted. The n-out-of-M-rule offers a more flexible compromise, where the trade-off between missed detection and false alarm rates may be more properly balanced, based on a particular application scenario.

In applying fusion rules, a consideration that warrants attention is the utilization of sensor statistics. While conventional fusion techniques, including n-out-of-M-rule, do not utilize the sensor statistics directly, it is evident that a detection rule needs to exploit the available statistical information in order to achieve optimality, especially when applied in a real implementation. To a certain extent, more recent works take into account the sensor statistics in optimizing the parameter n [9], [10]. Nevertheless, the fact that the sensors may have different accuracy is not directly accounted for in this optimization. Furthermore, given that the parameter statistics may vary in a realistic situation, the value of n would have to be accordingly adapted for optimality.

Other more statistically driven fusion methods include the maximum likelihood (ML) and maximum a posteriori (MAP) algorithms. The ML detection minimizes the sum of false alarm and missed detection rates; as such, it outperforms the optimized n-out-of-M-rule [11]. Similarly, the MAP algorithm minimizes the total probability of error. However, it should be noted that, for practical water monitoring applications, the probability of missed detection is typically more important than the probability of false alarm—a fact ignored by both the conventional ML and MAP algorithms.

In light of the above limitations of conventional data fusion in the context of water monitoring, this paper proposes a flexible MAP detector—that is nonetheless of low complexity—which minimizes the total cost imposed by false alarms and missed detections. In other words, by appropriately weighting these probabilities, a higher priority can be assigned to either quantity, to suit a particular application scenario; the proposed MAP detector then minimizes this weighted error rate.

The rest of this paper is organized as follows. The system model and problem definition are first presented in Sec. II. Then, fusion techniques based on the MAP algorithm, and their modifications, are described in Sec. III. Lastly, simulation results are reported in Sec. IV, with the conclusion in Sec. V.

II. System Model and Problem Definition

Consider a network with N total sensors, used to monitor the quality of water in a measurement area, e.g., a pool or a river. As discussed in the above, this area is hierarchically divided into multiple clusters, as illustrated in Fig. 1. However, since the present paper addresses phase 1 of the processing scheme, i.e., fusion in the LFC, the focus is on a single cluster, with M active sensors. Let θ denote the parameter to be measured, which, by cluster selection, should be nearly constant at all M sensors in the cluster. As noted previously, depending on the application, θ may represent quantities such as pH, DO, arsenic concentration, etc. Therefore, θ is generally a (bounded) continuous-valued quantity. Next, let e_m be the sensing error at the mth sensor. Then, the measured parameter can be modeled as

$$\hat{\theta}_m = g(\theta, e_m), \tag{1}$$

where $g(.)$ is a generalized function representing the sensor characteristic. With small errors in the sensor dynamic range, linear approximation provides the simplification

$$\hat{\theta}_m = \alpha_m \theta + e_m, \tag{2}$$

where $\alpha_m = 1$ if the sensors are properly calibrated.

At a particular sensor m, the measured $\hat{\theta}_m$ is compared with a selected range $[\tau_{\min}, \tau_{\max}]$: a bit $x_m = 1$ is sent to the LFC if the measured value is outside the safety range, otherwise $x_m = 0$ is sent to indicate safety. Decisions by the sensors in the cluster are transmitted to the LFC through orthogonal channels. Since the transmitted signal is narrow band, a flat fading channel model can be assumed. Let h_m be the Rayleigh flat fading channel for the link between mth sensor and the LFC, n_m its corresponding additive complex Gaussian noise, with variance σ_n^2. Using binary phased shift keying (BPSK) modulation, the received complex signal r_m at the LFC is

$$r_m = h_m(1 - 2x_m) + n_m. \tag{3}$$

Then, the optimum fusion problem involves finding the most probable value of x, given a set of M observations $\{r_m\}_{m=1}^{M}$. In this case, $x = 0$ means that water is safe in the measuring area, whereas $x = 1$ denotes contamination. Two fusion approaches can be defined based on soft detection or hard detection, as will be described in Sec. III.

At the sensor level, due to the precision of the mth sensor, two performance metrics can be defined: the probability of false alarm P_{F}^m (i.e., probability that the parameter of interest is in the allowed range, but the sensor detects it incorrectly as outside the range), and the probability of missed detection P_{M}^m (i.e., probability that the parameter is outside its allowed range, but the sensor is unable to detect the contamination). In other words,

$$P_{\mathrm{F}}^m = P\left(x_m = 1 | x = 0\right), \tag{4}$$

$$P_{\mathrm{M}}^m = P(x_m = 0 | x = 1). \tag{5}$$

Given specific distributions of the sensing parameter and sensing error in (2), the above performance metrics may be readily calculated.

Taking into account the wireless channel characteristic, the defined metrics are modified as follows:

$$\tilde{P}_{\mathrm{F}}^m = P_{\mathrm{F}}^m(1 - P_{\mathrm{b}}^m) + (1 - P_{\mathrm{F}}^m)P_{\mathrm{b}}^m, \tag{6}$$

$$\tilde{P}_{\mathrm{M}}^m = P_{\mathrm{M}}^m(1 - P_{\mathrm{b}}^m) + (1 - P_{\mathrm{M}}^m)P_{\mathrm{b}}^m, \tag{7}$$

where $\tilde{P}_{\mathrm{F}}^m$ and $\tilde{P}_{\mathrm{M}}^m$ are the equivalent probabilities of false alarm and missed detection respectively, and P_{b}^m is the bit error rate for signals received from the mth sensor, which depends on the quality of the channel from the mth sensor to the LFC.

More importantly, at the LFC level, the performance metrics can be defined based on x^{tot}, i.e., the total decision made by the LFC, as a result of the fusion scheme, so that

$$P_{\mathrm{F}}^{\mathrm{tot}} = P\left(x^{\mathrm{tot}} = 1 | x = 0\right), \tag{8}$$

$$P_{\mathrm{M}}^{\mathrm{tot}} = P(x^{\mathrm{tot}} = 0 | x = 1), \tag{9}$$

where $P_{\mathrm{F}}^{\mathrm{tot}}$ is referred to as the total probability of false alarm, and $P_{\mathrm{M}}^{\mathrm{tot}}$ as the total probability of missed detection. Furthermore, the total probability of error, $P_{\mathrm{E}}^{\mathrm{tot}}$, is defined as

$$P_{\mathrm{E}}^{\mathrm{tot}} = P\left(x^{\mathrm{tot}} = 1, x = 0\right) + P\left(x^{\mathrm{tot}} = 0, x = 1\right). \tag{10}$$

By substituting (8) and (9) into (10), while applying Bayes' rule,

$$P_{\mathrm{E}}^{\mathrm{tot}} = P_{H_1} P_{\mathrm{M}}^{\mathrm{tot}} + P_{H_0} P_{\mathrm{F}}^{\mathrm{tot}}, \tag{11}$$

where $P_{H_0} = P(x = 0)$ and $P_{H_1} = P(x = 1)$.

III. Fusion Techniques

Generally, the MAP method minimizes the total probability of error $P_{\mathrm{E}}^{\mathrm{tot}}$ defined in (11). In this section, two variants of MAP are first described, based on soft decision (SD) and hard decision (HD), respectively. Then, a Bayesian risk minimization approach is adopted to provide enhanced flexibility in managing different application requirements.

A. SD-MAP Fusion Algorithm

The SD-MAP fusion algorithm utilizes the set of M received signals in (3) to perform the following:

$$x^{\text{SD-MAP}} = \arg\max_x P(x | r_1, r_2, ..., r_{M-1}, r_M), \tag{12}$$

which admits a solution via an equivalent likelihood ratio (LR) test with the ratio ζ^{SD} [12]: if $\zeta^{\mathrm{SD}} > 1$ then $x^{\text{SD-MAP}} = 1$, otherwise $x^{\text{SD-MAP}} = 0$. In this case, the likelihood ratio ζ^{SD} is defined as

$$\zeta^{\mathrm{SD}} = \frac{P\left(x^{\mathrm{tot}} = 1\right)}{P\left(x^{\mathrm{tot}} = 0\right)}. \tag{13}$$

And applying Bayes' rule,

$$\zeta^{\mathrm{SD}} = \prod_{m=1}^{M} \frac{P(r_m | x = 1)}{P(r_m | x = 0)} \frac{P(x = 1)}{P(x = 0)}, \tag{14}$$

which expands to (15). Then, from (3), (4), and (5), the likelihood ratio ζ^{SD} is calculated by (16).

B. HD-MAP Fusion Algorithm

The HD-MAP fusion algorithm performs the following:

$$x^{\text{HD-MAP}} = \arg\max_x P(x | \hat{x}_1, \hat{x}_2, ..., \hat{x}_{M-1}, \hat{x}_M) \tag{17}$$

where $\hat{x}_m$ represents the hard decision of the received r_m. In this case, the likelihood ratio is

$$\zeta^{\mathrm{HD}} = \frac{P\left(x^{\mathrm{tot}} = 1\right)}{P\left(x^{\mathrm{tot}} = 0\right)} = \prod_{m=1}^{M} \frac{P(\hat{x}_m | x = 1)}{P(\hat{x}_m | x = 0)} \frac{P(x = 1)}{P(x = 0)}. \tag{18}$$

$$\zeta^{\mathrm{SD}} = \prod_{m=1}^{M} \left(\frac{P(r_m|x_m=1)P(x_m=1|x=1) + P(r_m|x_m=0)P(x_m=0|x=1)}{P(r_m|x_m=1)P(x_m=1|x=0) + P(r_m|x_m=0)P(x_m=0|x=0)} \right) \frac{P(x=1)}{P(x=0)}, \tag{15}$$

$$\zeta^{\mathrm{SD}} = \prod_{m=1}^{M} \left(\frac{\exp(-\frac{|r_m+h_m|^2}{\sigma_n^2})(1-P_{\mathrm{M}}^m) + \exp(-\frac{|r_m-h_m|^2}{\sigma_n^2})P_{\mathrm{M}}^m}{\exp(-\frac{|r_m+h_m|^2}{\sigma_n^2})P_{\mathrm{F}}^m + \exp(-\frac{|r_m-h_m|^2}{\sigma_n^2})(1-P_{\mathrm{F}}^m)} \right) \frac{P(x=1)}{P(x=0)}. \tag{16}$$

From (6) and (7), we observe in the right hand side of (18) that: if $\hat{x}_m = 1$, then $P(\hat{x}_m|x=1) = 1 - \tilde{P}_M^m$ and $P(\hat{x}_m|x=0) = \tilde{P}_F^m$; on the other hand, if $\hat{x}_m = 0$ then $P(\hat{x}_m|x=1) = \tilde{P}_M^m$ and $P(\hat{x}_m|x=0) = 1 - \tilde{P}_F^m$. Consequently

$$P(\hat{x}_m|x=1) = \hat{x}_m \left(1 - \tilde{P}_{\mathrm{M}}^m\right) + (1-\hat{x}_m)\tilde{P}_{\mathrm{M}}^m, \tag{19}$$

$$P(\hat{x}_m|x=0) = \hat{x}_m \tilde{P}_{\mathrm{F}}^m + (1-\hat{x}_m)\left(1 - \tilde{P}_{\mathrm{F}}^m\right), \tag{20}$$

from which (18) can be readily computed.

C. Fusion Algorithm with Risk Minimization

In the two MAP approaches developed so far, the objective function to be minimized in both cases is $P_{\mathrm{E}}^{\mathrm{tot}}$, defined in (11). As such, false alarms and missed detections receive the same priority. However, in water monitoring, the loss associated with a missed detection is far greater than that of a false alarm. A false alarm basically pushes the processing scheme (prematurely) into the second phase, where system resources such as bandwidth and power are wasted. By contrast, a missed detection is tantamount to potential health-related risks for the water users.

Therefore, a modified cost function which takes into the associated losses, as defined in the Bayesian risk minimization framework [12], can be formulated as follows,

$$\begin{aligned} \bar{C} &= C_{11}P_{H_1}(1-P_{\mathrm{M}}^{\mathrm{tot}}) + C_{01}P_{H_1}P_{\mathrm{M}}^{\mathrm{tot}} \\ &+ C_{10}P_{H_0}P_{\mathrm{F}}^{\mathrm{tot}} + C_{00}P_{H_0}(1-P_{\mathrm{F}}^{\mathrm{tot}}), \end{aligned} \tag{21}$$

where C_{ij} is the loss incurred for deciding H_i when H_j is true. Then, the optimum fusion rule which minimizes the risk (21) is achieved by modification of the LR ratio in either the SD- or HD-MAP algorithm as follows,

$$\zeta^{\text{Modified-HD}} = \frac{C_{01} - C_{11}}{C_{10} - C_{11}} \zeta^{\text{SD or HD}}. \tag{22}$$

IV. Simulation Results

In this section, simulation results for the conventional and modified SD- and HD-MAP algorithms are presented, and compared with other popular fusion rules such as MAX-rule and ML.

A. Case Study: pH Monitoring

For the purpose of exposition, the selected sensing parameter is a nearly ubiquitous quantity, which is routinely collected in WCWS, viz., the pH value. This parameter measures the acidity or alkalinity of water, with a nominal range of 0–14, where 7 represents neutrality. Values deviating significantly from 7 are considered unsafe. Therefore, a truncated Gaussian distribution can be used to statistically model the pH parameter. In addition, a uniform distribution is used to account for the quality differences in typical sensors. As such, corresponding to (2), the distributions of interest are

$$P(\theta) = \frac{\exp\left(-\frac{(\theta-\theta_0)^2}{2\sigma^2}\right)}{\sqrt{2\pi}\sigma\left[F(\frac{\theta_{max}-\theta_0}{\sigma}) - F(\frac{\theta_{min}-\theta_0}{\sigma})\right]}, \tag{23}$$

$$P(e_m) = \frac{1}{2\delta_m}, \qquad \text{if} \quad -\delta_m < e_m < +\delta_m, \tag{24}$$

where: for pH measurements, $\theta_{max} = 14$, $\theta_{min} = 0$, and $\theta_0 = 7$ are, respectively, the maximum, minimum, and neutral values; σ^2 represents the variance of the original Gaussian distribution (used in constructing the truncated distribution); and for the sensor error, δ_m indicates the maximum deviation of the measured signal from its actual value. It should be noted that, in this context, σ^2 represents the spread or variety of pH values that can be found in the measurement area. As such, σ^2 is henceforth referred to as the parameter diversity. Corresponding to these distributions, the prior probabilities can be calculated as

$$P_{H_0} = \frac{F(\frac{\tau_{max}-\theta_0}{\sigma}) - F(\frac{\tau_{min}-\theta_0}{\sigma})}{F(\frac{\theta_{max}-\theta_0}{\sigma}) - F(\frac{\theta_{min}-\theta_0}{\sigma})}, \tag{25}$$

$$P_{H_1} = 1 - P_{H_0}, \tag{26}$$

where, for potable water, the pH limits are typically selected to be $\tau_{max} = 8.5$ and $\tau_{min} = 6.5$, corresponding to the limits for alkalinity and acidity of the water, respectively. Fig. 2 shows P_{H_0} and P_{H_1} versus the parameter diversity. By substituting (23) and (24) into (4) and (5), P_{F}^m and P_{M}^m are also calculated, with the results illustrated in Fig. 3.

B. Simulation Setup

As mentioned before, in a WCWS, $P_{\mathrm{M}}^{\mathrm{tot}}$ is typically more important than $P_{\mathrm{F}}^{\mathrm{tot}}$; thus, the following loss assignment is made: $C_{11} = C_{00} = 0$, $C_{10} = 1$, and $C_{01} = 10$. Channel links are randomly generated from a Rayleigh distribution. The

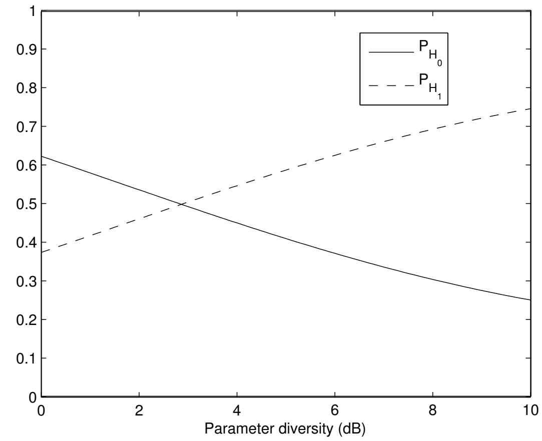

Fig. 2. P_{H_0} and P_{H_1} vs. parameter diversity.

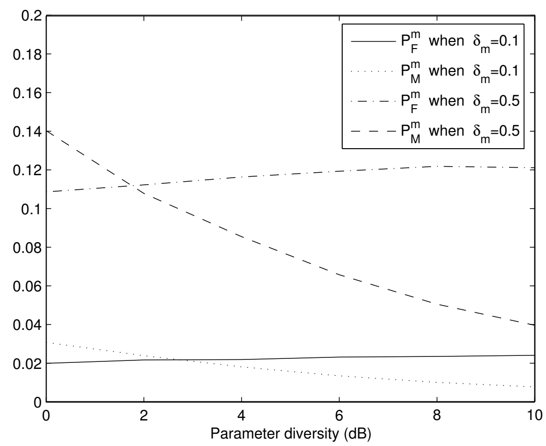

Fig. 3. P_{F}^m and P_{M}^m vs. parameter diversity.

measurement parameter and sensing error have distributions as defined by (23) and (24). For each sensor, δ_m is randomly generated, with the average in each cluster assumed to be $\bar{\delta}$ = 0.1, 0.2, and 0.5, i.e., in all cases $1 \geq \delta_m \geq 0$. Monte Carlo technique is used for simulations, with results averaged over 100,000 independent runs. The parameter diversity σ^2 varies from 0dB to 10dB. The average SNR for each sensor to LFC is 10 dB. $\bar{C}$ is considered as the performance criterion.

C. Results

Figures 4, 5, and 6 present $\bar{C}$ versus parameter diversity for $M = 5$ and $\bar{\delta} = 0.1$, 0.2 and 0.5. In all cases, the HD MAP algorithm performs very close to the SD MAP algorithm, and in the worst case, the HD MAP performs only 0.8 percent worse than the SD MAP algorithm. The modified HD MAP algorithm performs even much closer to the modified SD-MAP. Consequently, the HD based algorithms, which impose less computational complexity, are compelling choices.

In all cases, the modified MAP algorithms outperform the unmodified counterparts, so that the performance gain achieved through the modification of the MAP algorithms is about 25 percent for $\bar{\delta} = 0.1$ and 43 percent for $\bar{\delta} = 0.5$. However, in high values of parameter diversity, the SD- and HD-MAP algorithms perform only slightly better than ML. On the other hand, ML performs slightly better than MAX-rule. In most of the scenarios, the MAX-rule exhibits the worst performance.

By comparing Figures 4, 5, and 6, as can be expected, when $\bar{\delta}$ increases, the $\bar{C}$ increases too. Generally, $\bar{C}$ decreases with increasing parameter diversity (true in all figures, except for Fig. 8, with $\bar{\delta} = 0.5$ and $M = 20$). As the parameter diversity increases, the fusion rules have a higher chance to detect the existence of the contamination correctly. However, this observation only necessarily holds true when sensors of sufficient quality are employed. In fact, Figs. 7 and 8 show the results for sensors with poor quality, i.e., with large sensing errors. In Fig. 8, with low quality sensors, especially when $M = 20$ sensors are used, an increase in parameter diversity does not necessarily translate to improved accuracy of the fusion rules: there is an inherent lower bound for the performance, which is a function of $\bar{\delta}$. As such, even by increasing the number of sensors, the average cost is saturated and never falls bellow this limit. Therefore, for any desirable level of accuracy, the sensors must have a minimum quality; only then will we have a trade-off between the average sensor quality and the number of sensors.

V. Conclusion

In this paper, we proposed MAP based fusion rules for the application of WSNs in WCWSs. Conventional MAP algorithms give the same priority to false alarms and missed detections, which is not suitable for typical WCWSs. As such, a modified MAP approach, based on Bayesian risk minimization is proposed to allow for enhanced flexibility, e.g., higher loss assigned to missed detections. The proposed MAP and modified MAP algorithms are simulated and compared with conventional fusion rules. The obtained results demonstrate that the modified MAP algorithms exhibit significantly better performance, particularly in terms of the achieved average cost. This shows that the proposed methods are compelling candidates for water quality monitoring applications.

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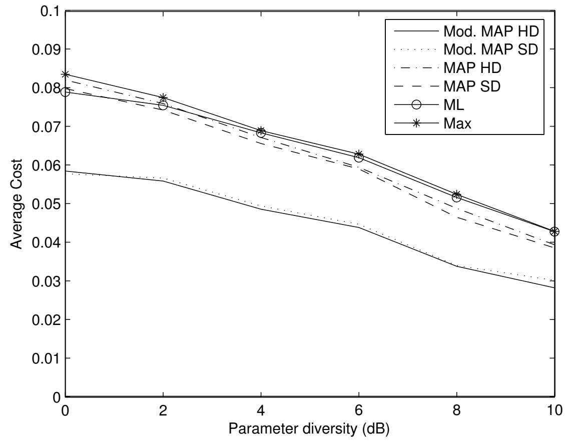

Fig. 4. Average cost vs. parameter diversity for M=5 and $\bar{\delta} = 0.1$.

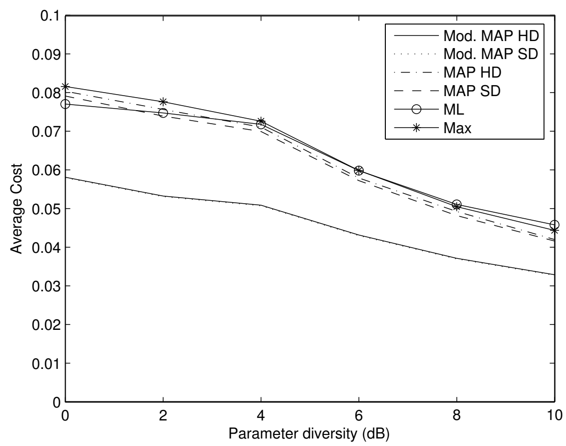

Fig. 5. Average cost vs. parameter diversity for M=5 and $\bar{\delta} = 0.2$.

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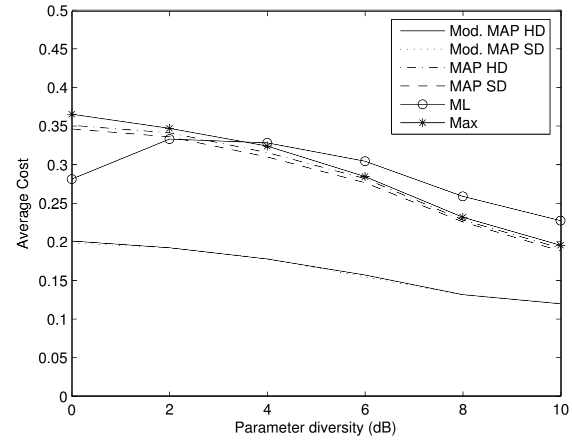

Fig. 6. Average cost vs. parameter diversity for M=5 and $\bar{\delta} = 0.5$.

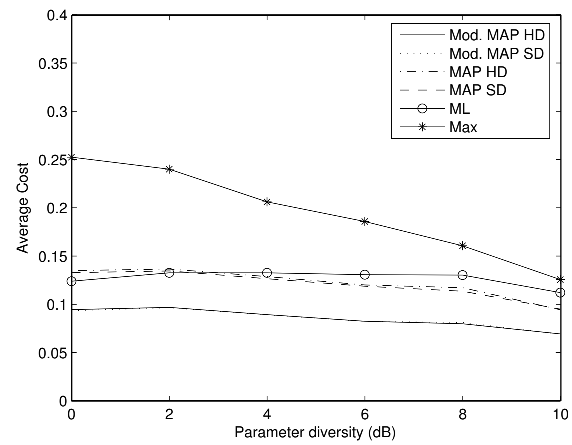

Fig. 7. Average cost vs. parameter diversity for M=10 and $\bar{\delta} = 0.5$.

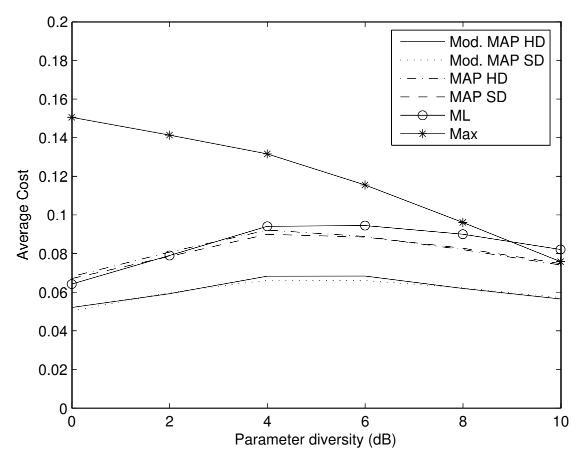

Fig. 8. Average cost vs. parameter diversity for M=20 and $\bar{\delta} = 0.5$..