Decentralized Sequential Change Detection Using Physical Layer Fusion

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***Abstract*— We study the problem of decentralized sequential change detection with conditionally independent observations. The sensors form a star topology with a central node called fusion center as the hub. The sensors transmit a simple function of their observations in an analog fashion over a wireless Gaussian multiple access channel and operate under either a power constraint or an energy constraint. Simulations demonstrate that the proposed techniques have lower detection delays when compared with existing schemes. Moreover we demonstrate that the energy-constrained formulation enables better use of the total available energy than a power-constrained formulation.**

I. Introduction

Wireless sensor networks can benefit from the broadcast and multi-access nature of wireless channels. Keeping this in mind, we design analog communication schemes over a discrete-time Gaussian multiple access channel (GMAC). In particular, we are interested in using such a scheme for decentralized change detection, *i.e.*, detection of a change in hypothesis over a wireless channel. While we focus on sequential change detection, our algorithms can be easily extended to sequential hypothesis testing. We consider a star topology with a central node called the fusion center as the hub. For simplicity, we assume a change from one Gaussian distribution to another, where both distributions have the same variance but different means. Our development in this paper can be extended to M hypotheses and arbitrary (known) distributions for the different hypotheses.

In order to exploit the superposition available in the GMAC, the sensors make an affine transformation of the observed data and transmit the output in an analog fashion over the GMAC. The motivation for using an affine transformation, even though it may be suboptimal in the present setting, is that the log-likelihood ratio is a sufficient statistic for the centralized change detection problem; for Gaussian observations, this turns out to be an affine function of the observations. Superposition in the GMAC provides a noisy version of this sufficient statistic.

We consider two cases: the sensors operate under either a power constraint or an energy constraint. The latter one is a better model for optimization because each sensor in reality is endowed with a constant total energy E and each transmission expends a certain amount of energy from this energy bank. This effectively captures both performance requirements and system costs in the optimization problem.

We now discuss relevant prior work. Page [1] studied change detection in a centralized setting. Shiryayev [2] studied the same problem in a Bayesian setting and provided a Markov decision framework. Veeravalli [3] used dynamic programming to solve the decentralized change detection problem with communication constraints that model transmission across a channel. Prasanthi [4] (see also [5]) considered the overall delay due to both random access and decision making. Our work differs from that of Veeravalli [3] and Prasanthi [4], [5] because we propose an analog communication strategy that exploits correlation in sensor observations and reduces decision delay.

Mergen and Tong [6] proposed a physical layer fusion technique called type-based multiple access for estimating a parameter over a GMAC. Their scheme also exploits the superposition available in the GMAC in a parameter estimation setting. Ertin and Potter [7] considered generalized cost functions that combine both the relative risks of decisions and the computational burden incurred in computing test statistics for automatic target recognition algorithms. This is mathematically similar to the energy-constrained formulation in Section IV.

The paper is organized as follows. In Section II, we formulate the change detection problem and solve it when the sensors have a power constraint. In Section III, we compare our scheme with that of Veeravalli [3]. In Section IV, we consider the energy-constrained formulation and compare this with the constant power case of Section II.

II. Physical Layer Fusion Framework

In this section, we focus on the change detection problem in a Bayesian setting. We obtain an optimal stopping rule and optimal parameters of the affine transformation for transmission over a GMAC, subject to a power constraint.

A. Mathematical Formulation

$X \sim \mathcal{N}(\theta, \sigma^2)$ indicates that X is Gaussian with mean θ and variance σ^2.

- The system has L sensors. At time k, sensor S_l makes an observation $X_{l,k} \sim \mathcal{N}(\theta_k, \sigma^2_{\mathsf{obs}})$, where θ_k is m_0 before the change and m_1 after the change, *i.e.*,

$$X_{l,k} = \theta_k + Z_{l,k}, \qquad (1)$$

where $Z_{l,k} \sim \mathcal{N}(0, \sigma^2_{\mathsf{obs}}), \quad l = 1, \ldots, L.$

- Each sensor transmits a function of its observation $\phi_{l,k}(X_{l,k}) = Y_{l,k}$. The function $\phi_{l,k}$ is an affine transformation that is the same for all sensors, *i.e.*

$$\phi_{l,k}(x) = \alpha_k (x - c_k). \qquad (2)$$

α_k and c_k are parameters for optimal control.

- The GMAC output received at the fusion center is

$$\widetilde{Y}_k = \sum_{l=1}^{L} Y_{l,k} + Z_{\mathsf{MAC},k}, \qquad (3)$$

where $Z_{\mathsf{MAC},k} \sim \mathcal{N}(0, \sigma^2_{\mathsf{MAC}})$, is independent and identically distributed (iid), and is independent of all other quantities.

- A change from hypothesis H_0 to H_1 occurs at random time Γ. Γ has the geometric distribution,

$$\Pr\{\Gamma = k | \Gamma > 0\} = p(1-p)^{k-1}, \quad k > 0, \qquad (4)$$

and $\Pr\{\Gamma = 0\} = \nu$ is the probability that the change occurred before the first observation is made.

- The observations at each sensor are independent, conditioned on the change time. Furthermore, the observations are independent from sensor to sensor, conditioned on the change time.
- At the fusion center, form $\widehat{Y}_k$ as follows:

$$\begin{aligned} \widehat{Y}_k &= \frac{1}{L\alpha_k}\left(\widetilde{Y}_k + L\alpha_k c_k\right) &(5)\\ &= \theta_k + \widehat{Z}_{\mathsf{MAC},k}, &(6) \end{aligned}$$

where

$$\widehat{Z}_{\mathsf{MAC},k} = \frac{1}{L}\sum_{l=1}^{L} Z_{l,k} + \frac{Z_{\mathsf{MAC},k}}{L\alpha_k} \sim \mathcal{N}(0, \sigma_k^2),$$

and

$$\sigma_k^2 = \frac{\sigma^2_{\mathsf{obs}}}{L} + \frac{\sigma^2_{\mathsf{MAC}}}{\alpha_k^2 L^2}. \qquad (7)$$

- The fusion center chooses an action $a_{k-1} \in \mathbb{A}$ at time $k-1$ from set of actions (controls) available

$$\mathbb{A} = \{stop\} \cup \{(continue, \alpha, c) : \alpha \in \mathbb{R}_+, c \in \mathbb{R}\}.$$

If $a_{k-1} = stop$, the fusion centre decides to stop. If $a_{k-1} = (continue, \alpha_k, c_k)$, the fusion center decides to take another sample (the kth), and all sensors transmit $\phi_{l,k}(X_{l,k})$ with parameters (α_k, c_k).

- As explained in [8], we assume a quasi-classical information structure, *i.e.*, the action a_{k-1} depends on

$$I_{k-1} = \left\{a_0, \widehat{Y}_1, a_1, \widehat{Y}_2, \ldots, a_{k-2}, \widehat{Y}_{k-1}\right\}. \qquad (8)$$

Even though the sensors may have local memory of past observations, our framework does not make use of this additional information. The fusion center feeds back the action parameters a_{k-1} to the sensors.

- The average power constraint at each sensor is given by

$$\mathbb{E}\left[\alpha_k^2 \left(X_{l,k} - c_k\right)^2 | I_{k-1}\right] \leq P, \qquad (9)$$

which simplifies to

$$\alpha_k^2 \left[\sigma^2_{\mathsf{obs}} + \mathbb{E}\left[\left(\theta_k - c_k\right)^2 | I_{k-1}\right]\right] \leq P. \qquad (10)$$

In Section IV, we will relax this and impose an expected total energy constraint.

- The fusion center policy π is a sequence of proposed (deterministic) actions $\pi = (\pi_{k-1}, k \geq 1)$, where π_{k-1} is a function $\pi_{k-1} : I_{k-1} \to \mathbb{A}$. Let τ be the first instant when the fusion center decides to stop.

Problem 1 (Change Detection with Delay Penalty): Minimize the expected detection delay, $E_{\mathsf{DD}} = \mathbb{E}\left(\tau - \Gamma\right)^+$, where $x^+ = \max(0, x)$, subject to an upper bound on the probability of false alarm $P_{\mathsf{FA}} = \Pr\{\tau < \Gamma\}$ and the power constraint in (10). □

In order to solve Problem 1, Shiryayev [2] proves that it is sufficient to solve Problem 2 given below. The optimal policy for Problem 1 is a solution to Problem 2 at an appropriate value of λ in (11).

Problem 2 (Change Detection with a Bayes Cost): Minimize the Bayes cost, $R(\lambda)$, over all admissible policies π, where

$$\begin{aligned} R(\lambda) &= P_{\mathsf{FA}} + \lambda E_{\mathsf{DD}} \\ &= \Pr\{\Gamma > \tau\} + \lambda \mathbb{E}\left[\sum_{k=0}^{\tau-1} \Pr\{\Gamma \leq k | I_k\}\right] \quad (11) \end{aligned}$$

and $\lambda > 0$ is the cost of unit delay. The expectation is taken with respect to the probability measure induced by the policy π. □

The equality in (11) follows from a result proved by Shiryayev in [2, pp.195–196]. This additive (with time) form of the Bayes cost in (11) along with the assumption of quasi-classical information structure makes Problem 2 amenable to a solution based on dynamic programming.

B. Solution to Problem 2

We first restrict the stopping time τ to a finite horizon T. Using the result from Bertsekas [9, Ch.1, Prop.3.1] [1], the cost-to-go functions can be written as

$$\begin{aligned} \tilde{J}_T^T(I_T) &= \Pr\{\Gamma > T | I_T\}, &(12)\\ \tilde{J}_k^T(I_k) &= \min\Big\{\Pr\{\Gamma > k | I_k\}, \lambda \Pr\{\Gamma \leq k | I_k\} \\ &\quad + \min_{\alpha_{k+1}, c_{k+1}} \mathbb{E}\left[\tilde{J}_{k+1}^T(I_{k+1}) | I_k\right]\Big\} &(13) \end{aligned}$$

for $0 \leq k \leq T-1$. We use "min" here anticipating Theorem 4 below which identifies a minimizing set of controls. We use $\tilde{J}$ to denote cost-to-go functions of the state I_k and let

[1]The above problem can be cast into a Markov decision problem with complete observations; this is implicitly shown in [3].

J denote cost-to-go functions of a sufficient statistic given in the following lemma.

Lemma 1: $\tilde{J}_k^T(I_k)$ depends on I_k only through the sufficient statistic

$$\mu_k \triangleq \Pr\{\Gamma \leq k | I_k\}, \tag{14}$$

the a posteriori probability that the change has occurred. We may therefore write $\tilde{J}_k^T(I_k) = J_k^T(\mu_k)$. □

Observe that $\mu_0 = \nu$ and that

$$\beta_k \triangleq \Pr\{\Gamma \leq k+1 | I_k\} = \mu_k + (1-\mu_k)p. \tag{15}$$

It can be shown that the following recursive equation holds for μ_k.

$$\begin{aligned}
\mu_{k+1} &= \Pr\{\Gamma \leq k+1 | I_{k+1}\} \\
&= \frac{\beta_k f_{m_1,\alpha_{k+1}}(\hat{y}_{k+1})}{\beta_k f_{m_1,\alpha_{k+1}}(\hat{y}_{k+1}) + (1-\beta_k) f_{m_0,\alpha_{k+1}}(\hat{y}_{k+1})} \quad (16)\\
&\triangleq \frac{g(\hat{y}_{k+1}, \alpha_{k+1}, \mu_k)}{h(\hat{y}_{k+1}, \alpha_{k+1}, \mu_k)}, \quad (17)
\end{aligned}$$

where

$$f_{m_i,\alpha_{k+1}}(\hat{y}_{k+1}) \triangleq \frac{1}{\sqrt{2\pi\sigma_{k+1}^2}} \exp\left\{ -\frac{(\hat{y}_{k+1} - m_i)^2}{2\sigma_{k+1}^2} \right\} \tag{18}$$

for $i = 1, 2$. The variance σ_{k+1}^2 depends on α_{k+1} as shown in (7), and hence the dependence on α_{k+1} in (17). Note that (17) depends on c_{k+1} only through α_{k+1} because of the processing done in (5). Also, the optimal controls at time $k+1$, α_{k+1} and c_{k+1}, depend on I_k only through μ_k. Thus the fusion center needs to keep only $\mu_k \in [0,1]$ in its memory instead of the $2k$-tuple I_k.

As a consequence of the above lemma, we can write (12) and (13) directly as functions of μ_k as follows:

$$\begin{aligned}
J_T^T(\mu_T) &= 1 - \mu_T, \quad (19)\\
J_k^T(\mu_k) &= \min\left\{1 - \mu_k, \lambda\mu_k + A_k^T(\mu_k)\right\}, \quad (20)
\end{aligned}$$

where

$$A_k^T(\mu) = \min_{\alpha} \int_{\mathbb{R}} J_{k+1}^T\left(\frac{g(\hat{y},\alpha,\mu)}{h(\hat{y},\alpha,\mu)}\right) h(\hat{y},\alpha,\mu)\, d\hat{y} \tag{21}$$

for $0 \leq k \leq T-1$.

To solve Problem 2, we let the horizon $T \to \infty$. From results in [8] and [3], the following limit exists and is independent of k. The stationarity of the cost-to-go function follows from the memoryless nature of geometric distribution. The infinite horizon cost-to-go function is given by

$$\begin{aligned}
J(\mu) &= \lim_{T\to\infty} J_k^T(\mu) \quad (22)\\
&= \min\left\{1 - \mu, \lambda\mu + A_J(\mu)\right\}, \quad (23)
\end{aligned}$$

where

$$A_J(\mu) = \min_{\alpha} \int_{\mathbb{R}} J\left(\frac{g(\hat{y},\alpha,\mu)}{h(\hat{y},\alpha,\mu)}\right) h(\hat{y},\alpha,\mu)\, d\hat{y}. \tag{24}$$

The following lemma gives some properties of the finite horizon and infinite horizon cost-to-go functions.

Lemma 2: The functions $J_k^T(\mu)$ and $A_k^T(\mu)$ are nonnegative and concave functions of μ, for $\mu \in [0,1]$. Also, $A_k^T(1) = J_k^T(1) = 0$. Similarly, the functions $J(\mu)$ and $A_J(\mu)$ are nonnegative and concave functions of μ, for $\mu \in [0,1]$, and $A_J(1) = J(1) = 0$. □

We can show an interesting characterization of $A_J(\mu)$ in terms of an Ali-Silvey distance (defined in [10]), which is useful in the sequel. Its proof is omitted for brevity.

Theorem 3: The minimization in (24) can be expressed as maximization of an Ali-Silvey distance between the density functions $f_{m_1,\alpha}$ and $f_{m_0,\alpha}$. □

The above theorem establishes the following intuitively obvious fact: the optimal control at any time should be chosen to maximize the Ali-Silvey distance between the two hypotheses before and after the change. Since Ali-Silvey distances satisfy the data processing inequality (see for example [11]), data processing cannot improve our ability to detect a change.

We now identify the optimal stopping policy at the fusion center as well as the optimal controls α and c.

Theorem 4: An optimal fusion center policy has stopping time τ given by

$$\tau = \inf\{k : \mu_k \geq a\}, \tag{25}$$

where a is the unique solution to

$$\lambda a + A_J(a) = 1 - a. \tag{26}$$

The optimal control at time $k+1$ is given by

$$\begin{aligned}
c_{k+1} &= \mathbb{E}\left[\theta_{k+1} | I_k\right] = m_1\beta_k + m_0(1-\beta_k), \quad (27)\\
\alpha_{k+1}^2 &= \frac{P}{\sigma_{\mathsf{obs}}^2 + \mathsf{Var}\left\{\theta_{k+1} | I_k\right\}}\\
&= \frac{P}{\sigma_{\mathsf{obs}}^2 + (m_1 - m_0)^2\beta_k(1-\beta_k)}, \quad (28)
\end{aligned}$$

where β_k is as in (15). □

Proof: We only outline a proof. The first part follows from (23) and Lemma 2. To show the second part, we first show that the largest α that meets the power constraint is the right choice. Indeed, any smaller choice results in an output which is a stochastically degraded version of the output obtained with the largest α. We then use the fact that $A_J(\mu)$ is the maximum of an Ali-Silvey distance and that data processing only degrades performance. ■

This theorem confirms yet another intuitively obvious control: set c_{k+1} to remove any a posteriori bias in the observation $X_{l,k+1}$ and set α_{k+1} to utilize all the available power.

C. A Simpler Suboptimal Policy

The choice of an affine transformation $\phi_{l,k}(x) = \alpha_k(x - c_k)$ in (2) may be suboptimal. Within the constraints of this affine set of controls we have identified the optimal (α, c) at each stage. Let us now further restrict the controls to be of the following form: the decision to stop or continue depends on I_k, but the parameters of the affine transformation at time $k+1$ can only depend on I_0 and $b_k \in \{stop, continue\}$. I_0 denotes the prior information before any observations are made and b_k is the decision of the fusion center at k.

As suggested by the structure of the controls in Theorem 4, we propose the following new set of controls:

$$c_{k+1} = m_1\beta_k + m_0(1-\beta_k), \quad (29)$$

$$\alpha_{k+1}^2 = \frac{P}{\sigma_{\textsf{obs}}^2 + (m_1-m_0)^2\beta_k(1-\beta_k)}, \quad (30)$$

where now $\beta_k = \Pr\{\Gamma \leq k+1 | I_0\} = 1-(1-\nu)(1-p)^{k+1}$.

III. Comparison of Performance

In this section we compare the performances of our policies in Theorem 4, the suboptimal policy in Section II-C, and that of Veeravalli [3] in terms of mean detection delay and probability of false alarm.

Veeravalli [3] addresses the structure of optimal D_l-level quantizer at sensor $S_l, l = 1, 2, \ldots, L$. His model is applicable to a system that allows $\log_2 D_l$ bits to be sent error free from sensor S_l to the fusion center. For simplicity let $D_l = D, l = 1, 2, \ldots, L$. If this scheme is employed on a GMAC with a unit delay per sample, each sensor transfers $\log_2 D$ bits per sample to the fusion center. Thus the $\textsf{SNR} = P/\sigma_{\textsf{MAC}}^2$ required to support transmission at this rate on the GMAC satisfies the sum rate constraint

$$L \log D \leq \frac{1}{2}\log\left(1 + L\cdot\textsf{SNR}\right), \quad (31)$$

and thus

$$\textsf{SNR} \geq \frac{D^{2L}-1}{L}. \quad (32)$$

The constraint (31) assumes that the data from the sensors are independent and that the multi-access strategy does not make use of the correlatedness in the sensor observations.

Observe that Veeravalli's optimal algorithm requires feedback of $\mu_k \in [0,1]$ with the D-level quantizer thresholds computed at the sensors.[2] Alternatively, the fusion center may perform this calculation and inform each sensor the set of $D-1$ thresholds ($\in \mathbb{R}^{D-1}$) and a decision to stop or continue. Our proposed scheme requires the binary decision and two real-valued variables (α, c) to be fed back. The strategy in Section II-C requires only the binary decision to be fed back.

Consider two sensors with one-bit quantizers ($L = 2, D = 2$). Equation (32) implies $\textsf{SNR} \geq 7.5$ for Veeravalli's algorithm to be feasible on the GMAC. All algorithms operate on the GMAC with $\textsf{SNR} = 7.5$. We use the following parameters:

Simulation Setup 1: Consider 2 sensors with $\mathcal{N}(0,1)$ and $\mathcal{N}(0.75,1)$ observations before and after the change, respectively. The geometric parameter $p = 0.05$ and the initial probability of change $\nu = 0$. □

Figure 1 shows that both our algorithms give lesser delays than Veeravalli's algorithm on the GMAC. Furthermore, the suboptimal policy of Section II-C degrades from that in Theorem 4 only for the low $P_{\textsf{FA}}$ scenario. The network delay is independent of the number of sensors in both our algorithms; the performance improves with increasing number of sensors. Veeravalli's scheme on the other hand requires an exponential growth in $\textsf{SNR}$ (with L, as in (32)) to maintain the same delay - $P_{\textsf{FA}}$ performance. However, our algorithms need fine-grained synchronization, power balance at the fusion center, and phase alignment for proper beamforming at the fusion center. These can be achieved via downlink beacons and downlink-uplink reciprocity as is possible in the slotted version of the IEEE 802.15.4 MAC/PHY standard.

[2]Each sensor knows its index l.

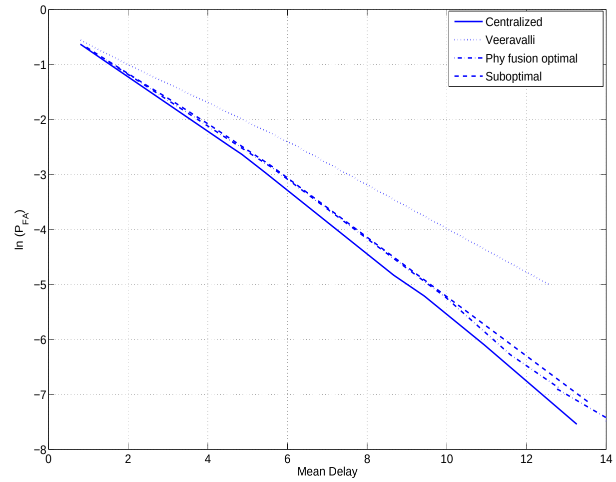

Fig. 1. Comparison of our algorithms with Veeravalli's scheme.

IV. Energy-Constrained Formulation

In this section, we develop the solution for an energy-constrained formulation of the problem solved in Section II.

Problem 3: Minimize the expected detection delay, $E_{\textsf{DD}}$, subject to an upper bound on the probability of false alarm, $P_{\textsf{FA}}$, and an upper bound on the expected energy spent,

$$\mathbb{E}\left[\sum_{k=1}^{\tau}\mathbb{E}\left[\phi_{l,k}^2(X_{l,k})|I_{k-1}\right]\right] \leq E, \quad l = 1, 2, \ldots, L. \quad (33)$$

□

Let $\lambda = (\lambda_1, \ldots, \lambda_L, \lambda_{L+1})$. As before, to solve Problem 3, we set up the Bayes cost $R(\lambda)$ and minimize it over all admissible choices of stopping policy and the parameters of the affine transformation, $\phi_{l,k}$, *i.e.*, α_k and c_k. The Bayes cost can be written as

$$R(\lambda) = \Pr\{\Gamma > \tau\} + \mathbb{E}\Big[\lambda_{L+1}\sum_{k=0}^{\tau-1}\Pr\{\Gamma \leq k | I_k\} + \sum_{k=1}^{\tau}\sum_{l=1}^{L}\lambda_l\mathbb{E}\left[\alpha_k^2(X_{l,k}-c_k)^2|I_{k-1}\right]\Big]. \quad (34)$$

As in Section II-B, we can show that the optimal stopping policy is the same as in Theorem 4, and that the optimal control at time $k+1$, given I_k, is

$$c_{k+1} = m_1\beta_k + m_0(1-\beta_k), \quad (35)$$

$$\alpha_{k+1} = \arg\min_{\alpha}\Big[\alpha^2\left(\sigma_{\textsf{obs}}^2 + (m_1-m_0)^2\beta_k(1-\beta_k)\right)\lambda_0 + \int_{\mathbb{R}} J\left(\frac{g(\hat{y},\alpha,\mu_k)}{h(\hat{y},\alpha,\mu_k)}\right)h(\hat{y},\alpha,\mu_k)\,d\hat{y}\Big], \quad (36)$$

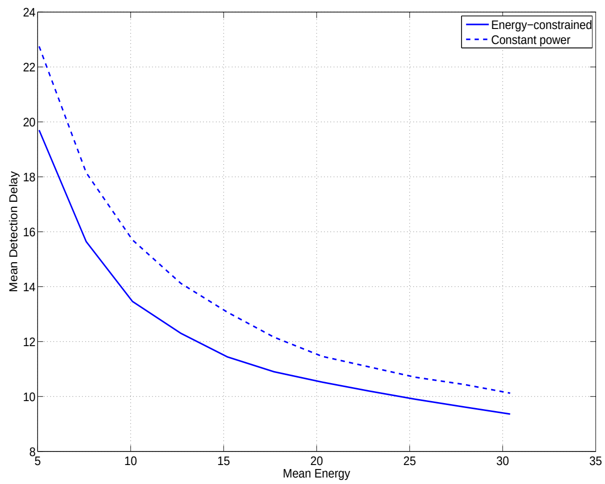

Fig. 2. Comparison of constant power method and energy-constrained method.

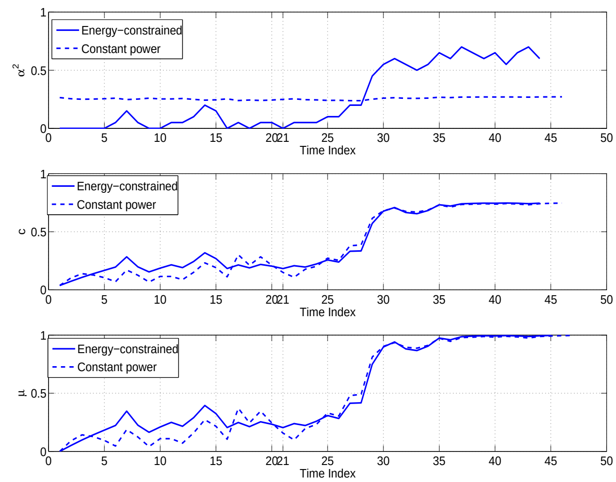

Fig. 3. α^2, c, and μ of constant power method and energy-constrained method for a sample path.

where $\lambda_0 = \sum_{l=1}^{L} \lambda_l$, and $J(\mu)$ is the infinite horizon cost-to-go function

$$J(\mu) = \min \left\{1 - \mu, \lambda_{L+1}\mu + A_J(\mu)\right\}, \qquad (37)$$

with

$$\begin{aligned} A_J(\mu) &= \min_{\alpha} \Big[\alpha^2 \left(\sigma_{\mathsf{obs}}^2 + (m_1 - m_0)^2 \beta(1-\beta)\right) \lambda_0 \\ &\quad + \int_{\mathbb{R}} J\left(\frac{g(\hat{y}, \alpha, \mu)}{h(\hat{y}, \alpha, \mu)}\right) h(\hat{y}, \alpha, \mu)\, d\hat{y}\Big]. \end{aligned} \qquad (38)$$

A. Comparison with Power-Constrained Formulation

Here, we compare the performances of the constant power solution and the energy-constrained one. We use the parameters in Simulation Setup 1.

For $P_{\mathsf{FA}} \leq e^{-4}$, we first identify the minimum time to detect change as a function of the energy constraint. This indicates a power constraint under the constant power formulation. We then compare the delays incurred by the optimal algorithm under the two formulations in Figure 2. For the same P_{FA}, the energy-constrained solution declares a change with lesser delay than the constant power solution.

As an illustration, we plot in Figure 3 the variation of α^2, c and μ with time in both the algorithms for a representative sample path. We use the same parameters as in Simulation Setup 1. The change point is at 21 samples, shown using a dotted vertical grid line. The energy-constrained solution is more energy efficient because it uses lower energy (α^2) before and higher energy after the change point. Indeed, based on the prior information, the first few samples use negligible energy. This algorithm also stops earlier than the constant power algorithm (on this typical sample path).

V. Conclusion

We formulated and solved the decentralized change detection problem over a GMAC for an affine transmission strategy. We exploited superposition in the physical layer to achieve superior delay performances. We further saw that the energy-constrained solution decides on the change with lesser delay than the constant power solution for the same false alarm rate.

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