Abnormality Detection Inside Blood Vessels with Mobile Nanomachines

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***Abstract*—Motivated by the numerous healthcare applications of molecular communication within Internet of Bio-Nano Things (IoBNT) paradigm, this work addresses the problem of abnormality detection in a blood vessel using multiple biological embedded computing devices called cooperative biological nanomachines (CNs), and a common receiver called the fusion center (FC). Due to blood flow inside a vessel, each CN and the FC are assumed to be mobile. In this work, each CN performs abnormality detection with certain probabilities of detection and false alarm. The CNs report their local decisions to a FC over a diffusion-advection blood flow channel using different types of molecules in the presence of inter-symbol interference, multi-source interference, and counting errors. The FC employs the OR and AND logic based fusion rules to make the final decision after decoding the local decisions using the sub-optimal detectors based on the approximation of the log-likelihood ratio. For the aforementioned system, probabilities of detection and false alarm at the FC are derived. Finally, simulation results are presented to validate the derived analytical results, which provide important insights.**

***Index Terms*—Abnormality detection, diffusion, IoBNT, mobility, molecular communication, nano-networks.**

I. Introduction

THE Internet of Bio-Nano Things (IoBNT) paradigm is gaining significant prominence for addressing challenging problems in biomedical scenarios [1], where biological cells, produced through synthetic biological processes, are used as biological embedded computing devices or nanomachines to perform sensing, and actuation etc. Based on the biological cells and their functionalities in the biochemical domain, biological nanomachines have led to the development of novel applications such as intra-body sensing and actuation, intra-body connectivity control, efficient drug delivery, gene therapy, artificial blood cell production, and human body monitoring by an external health-care provider (see [2]–[4] and the references therein). However, this paradigm poses several research challenges in terms of communication and networking using biochemical infrastructure while enabling an interface to the Internet. Development of efficient and safe techniques for information exchange, interaction, and networking between the biological nanomachines within the IoBNT, is one of the major research challenges. In this context, molecular communication involving transmission and reception of information encoded in molecules, has attracted significant research attention in the field of IoBNT [5]–[12]. Molecular communication which is naturally carried out by cells without external influence is ideally suited for above applications especially for abnormality or anomaly detection inside the blood vessels at nano-scale [13].

Recently, some research efforts [14]–[19] have been devoted to addressing abnormality detection such as tumor, and cancer, etc. However, none of the works considered the abnormality detection problem in a diffusion-advection blood flow channel, where multiple cooperative biological nanomachines (CNs) and a common receiver or fusion center (FC) also move along with the information molecules with blood flow. This work, therefore, addresses the abnormality detection problem in a blood vessel where each of the mobile CNs are assumed to perform abnormality detection with certain probability of detection and probability of false alarm and report the local decisions to a FC using different types of molecules. Simple OR and AND fusion rules are employed at the FC to infer the presence or absence of the abnormality after decoding the local decisions transmitted by each of the CNs over a flow-induced diffusive channel in the presence of inter-symbol interference (ISI), multi-source interference (MSI), and counting errors. In contrast to the Chair-Varshney (CV) rule [20]–[22], the performance of AND/OR rules at the FC can be characterized in terms of closed-form expressions for the probabilities of detection and false alarm. Using the first hitting time model, the probabilities of detection and false alarm at the FC are derived employing OR and AND logic based fusion rules, incorporating the detection performance of the CNs. Here, the first hitting time model best captures the randomness of the arrival time of the molecule due to the Brownian motion of the CNs and FC to make a final decision on abnormality. It is also worth mentioning that in contrast to the passive receiver considered in the existing literature, this work models the receiver nanomachines as fully absorbing receivers [23], [24] which is more practical for health-care applications inside the human body.

II. System Model

This work considers cooperative abnormality detection using molecular signaling inside a blood vessel, i.e., semi-infinite one-dimensional flow-induced fluid medium with constant temperature and viscosity, where the length of propagation is large compared to width dimensions. Due to blood flow inside a vessel, all of the CNs and FC are assumed to be mobile[1] with the flow v, i.e., $v_{\text{CN},k} = v_{\text{FC}} = v$, where $v_{\text{CN},k}$ and v_{FC} denote the velocities of the kth CN and the

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[1]Similar to [25]–[27], the movement of each CN and the FC is modeled as a one dimensional Gaussian random walk, where each of the nanomachines (CNs and FC) are released simultaneously inside the blood vessel. It is assumed that the movement of each CN and the FC does not disrupt the propagation of the information molecules. Moreover, the CNs and the FC can pass each other (see [27] for detailed information).

FC, respectively, where $1 \leq k \leq K$. The diffusion coefficient of the kth mobile CN, located at distance $d_{0,k}$ from the FC at $\tau = 0$, is denoted by $D_{\text{CN},k}$, whereas the diffusion coefficient of the FC is denoted by D_{FC}. One promising application of this work is chrono drug-delivery [28], where CNs detect an event indicating the abnormality inside the blood vessel. For example, each of the CNs can detect the same or different events indicating abnormality by sensing the molecules[2] released from one or more infected tissues. This work considers independent observations at each of the CNs as applicable to various scenarios that include cancer detection in which different CNs can sense (or measure) different gene and protein based biomarkers, nucleic/ amino acids, and a lack of oxygen [17], [29], [30]. Subsequently, each CN independently communicates its local decision to the drug delivery nanomachine, i.e., FC, which decodes each CN decision to collectively decide the presence of abnormality so as to release the drug inside the blood vessel. The procedure for cooperative abnormality detection is given below.

- **Step 1:** Depending on the processing capability, each CN can employ a different decision rule for abnormality detection in the jth time-slot, $j \in \{1, 2, \cdots\}$. The detection performance[3] of the kth CN is characterized in terms of its probabilities of detection ($P_{D,k}^{\text{CN}}$) and false alarm ($P_{F,k}^{\text{CN}}$).
- **Step 2:** Next, using different types of molecules[4], each CN transmits its local decision obtained in Step 1 to the FC in the subsequent $(j+1)$th time-slot only if it detects an abnormality otherwise it remains silent.
- **Step 3:** The FC first decodes the local decisions transmitted by each CN over the potentially erroneous diffusive channel using the sub-optimal detector based on the approximation of the log-likelihood ratio. Finally, the FC combines the decoded binary decisions using AND/OR rules to make a final decision to infer the absence or presence of an abnormality inside a blood vessel.

Similar to several existing works [32]–[36] and the references therein, this work also assumes perfect time synchronization between the CNs and the FC to develop various important insights into the system performance. The channel is divided into time-slots of duration τ, where the $(j+1)$th slot is defined as the time period $[j\tau, (j+1)\tau]$ with $j \in \{1, 2, \cdots\}$ and the individual time-slot is comprised of N sub-slots of duration $\tilde{\tau}$. This work also assumes that the abnormality exists either in all N sub-slots of total duration $N\tilde{\tau}$ or none and the observations in the successive time-slots are assumed independent [18], [37]. Hence, each CN senses the channel for N consecutive sub-slots to take a decision. Upon receiving the local decision from each CN, the FC makes an overall decision at the end of each time-slot of duration τ. The number of molecules received at the FC corresponding to the transmission of local decision $x_k[j] \in \{0, 1\}$ by the kth CN in slot $[j\tau, (j+1)\tau]$ can be expressed as

$$\widetilde{R}_k[j+1] = \widetilde{S}_k[j+1] + \widetilde{\mathcal{I}}_k[j+1] + \widetilde{N}_k[j+1] + \widetilde{C}_k[j+1], \quad (1)$$

where $\widetilde{S}_k[j+1]$ represents the number of molecules received in the current $(j+1)$th slot and follows a binomial distribution with parameters $n_k x_k[j]$ and q_k^0, i.e., $\mathscr{B}(n_k x_k[j], q_k^0)$, where n_k is the number of type-k molecules transmitted by the kth CN for $x_k[j] = 1$ and q_k^0 denotes the probability that a transmitted molecule reaches the FC within the current slot. The quantity $\widetilde{N}_k[j+1]$ denotes MSI, i.e., background noise arising due to molecules received from other sources, which can be modeled as a Gaussian distributed random variable with mean μ_o and variance σ_o^2 under the assumption that the number of interfering sources is sufficiently large [38]. The approximation still holds for the scenarios when the number of interfering sources is not sufficiently large but they are close to the intended receiver and transmit a large number of interfering molecules [38, Section IV]. Also, note that the noise $\widetilde{N}_k[j+1]$ and the number of molecules $\widetilde{S}_k[j+1]$ received from the intended CN are independent [32]. The term $\widetilde{C}_k[j+1]$ denotes the error in counting the type-k molecules at the FC, also termed as the "counting error". This can be modeled as a Gaussian distributed random variable with zero mean and variance that depends on the average number of molecules received as, $\sigma_{c,k}^2[j+1] = \mathbb{E}\{\widetilde{R}_k[j+1]\} = n_k x_k[j] q_k^0 + \mu_o + \sum_{i=2}^{j} n_k x_k[j-i+1] q_k^{i-1}$ [32], [39]. The quantity $\widetilde{\mathcal{I}}_k[j+1]$ is the ISI arising in slot $j+1$ due to transmissions in the previous slots and is given as

$$\widetilde{\mathcal{I}}_k[j+1] = \widetilde{I}_k[2] + \widetilde{I}_k[3] + \cdots + \widetilde{I}_k[j], \quad (2)$$

where $\widetilde{I}_k[i] \sim \mathscr{B}(n_k x_k[j-i+1], q_k^{i-1}), 2 \leq i \leq j$ denotes the number of stray molecules received corresponding to the transmission of binary decision $x_k[j-i+1] \in \{0, 1\}$ in the $(j-i+2)$th slot. Moreover, the probability q_k^{j-i} that a molecule transmitted by the kth CN in slot $i \in \{1, 2, \cdots, j\}$ arrives at FC during time-slot j can be obtained as [34, Eq. (1)], $q_k^{j-i} = \int_{(j-i)\tau}^{(j-i+1)\tau} f_k(t; i) dt$, where $\tau = N\tilde{\tau}$ and $f_k(t; i)$ is the probability density function (PDF) of the first hitting time, i.e., the time required for a molecule to reach the FC. The PDF $f_k(t; i)$ for a flow-induced diffusive channel considering mobile kth CN and FC with flow v, i.e., $v_{\text{CN},k} = v_{\text{FC}} = v$, $D_{\text{CN},k} \neq 0$, and $D_{\text{FC}} \neq 0$, is given by[5] [27, Eq. (16)]

$$f_k(t; i) = \frac{[i\tau D_{\text{tot},k} D]^{1/2}}{\pi \sqrt{t} w_k(t; i)} e^{\left(\frac{-d_{0,k}^2}{4i\tau D_{\text{tot},k}}\right)} + e^{\left(\frac{-d_{0,k}^2}{4D u_k(t;i)}\right)} \times \frac{d_{0,k}}{\sqrt{4\pi D (u_k(t; i))^3}} \text{erf}\left(\frac{d_{0,k}\sqrt{tD}}{2\sqrt{i\tau D_{\text{tot},k} w_k(t; i)}}\right), \quad (3)$$

where $u_k(t; i) \triangleq t + i\tau D_{\text{tot},k}/D$ and $w_k(t; i) \triangleq i\tau D_{\text{tot},k} + tD$. The distance $d_{0,k}$ is the Euclidean distance between the kth CN and the FC at time $\tau = 0$, $\text{erf}(x)$ denotes the

[2]The molecules released from an infected tissue are different from the information carrying molecules between each of the CNs and FC.

[3]This work considers $P_{D,k}^{\text{CN}}[j] = P_{D,k}^{\text{CN}}, P_{F,k}^{\text{CN}}[j] = P_{F,k}^{\text{CN}}, \forall j$ since it is assumed that the characteristics of the channel between the source and the kth CN do not change over time. It is also worth noting that similar to hitting probabilities [31], $P_{D,k}^{\text{CN}}$ and $P_{F,k}^{\text{CN}}$ at the FC can be estimated at the beginning of the communication process using known training sequences.

[4]The molecular propagation of type-k molecules from the kth CN to the FC occurs via Brownian motion with drift and diffusion coefficient D_{P}.

[5]The derived PDF is also verified through particle-based simulations in [27]. It is worth noting that the PDF in (3) is equivalent to the first hitting time PDF [25, Eq.(6)] for diffusion channels without flow and mobile CNs and FC. This is due to the fact that the effective flow velocity, i.e., $v - v_{\text{FC}}$, considering the relative motion between the information molecules and the FC, is zero as FC is moving with the same flow v i.e., $v_{\text{FC}} = v$.

standard error function and the quantities $D_{\text{tot},k}$ and D are defined as, $D_{\text{tot},k} = D_{\text{CN},k} + D_{\text{FC}}$ and $D = D_{\text{FC}} + D_{\text{P}}$ respectively. Further, if the number of molecules released by the kth CN satisfy $n_k q_k^0 > 5$ and $n_k(1-q_k^0) > 5$ [32], the binomial distribution for $\widetilde{S}_k[j+1]$ can be approximated by the Gaussian distribution[6] with mean $\mu_k[j+1] = n_k x_k[j] q_k^0$ and variance $\sigma_k^2[j+1] = n_k x_k[j] q_k^0(1-q_k^0)$, i.e., $\widetilde{S}_k[j+1] \sim \mathcal{N}(n_k x_k[j] q_k^0, n_k x_k[j] q_k^0(1-q_k^0))$ [40]. Similarly, the binomial distribution of $\widetilde{I}_k[i], 2 \leq i \leq j$ can be approximated as $\widetilde{I}_k[i] \sim \mathcal{N}(\mu_{I,k}[i]{=}n_k x_k[j-i+1] q_k^{i-1}, \sigma_{I,k}^2[i]{=}n_k x_k[j-i+1] q_k^{i-1}(1-q_k^{i-1}))$. Further note that $\widetilde{S}_k[j+1]$ and $\widetilde{I}_k[i], i = 2, 3, \cdots, j$ are independent since the molecules transmitted in different time slots do not interfere with each other [32], [33]. Based on the system model discussed above, the AND and OR logic based rules at the FC are defined as, *AND rule:* there is abnormality if the decisions obtained from all the CNs report an abnormal state. *OR rule:* there is abnormality if at least one decision obtained at the FC reports an abnormal state.

III. Detection Performance Analysis at FC

Let $\mathcal{H}_0$ and $\mathcal{H}_1$ denote the hypotheses corresponding to the absence and presence of abnormality inside a blood vessel. The average probability of detection Q_D^l and probability of false alarm Q_F^l at the FC corresponding to CN transmissions in time-slots 1 to l are given as

$$Q_D^l = \frac{1}{l}\sum_{j=1}^{l} Q_D[j+1], \qquad Q_F^l = \frac{1}{l}\sum_{j=1}^{l} Q_F[j+1], \tag{4}$$

where $Q_D[j+1]$ and $Q_F[j+1]$ denote the probabilities of detection and false alarm at the FC corresponding to the transmission by each of the CNs in the $(j+1)$th time-slot. The closed-form expressions for $Q_D[j+1]$ and $Q_F[j+1]$ are derived next for AND and OR fusion rules at the FC.

1) AND Rule: The probabilities of detection $Q_D[j+1]$ and false alarm $Q_F[j+1]$ at the FC corresponding to the transmission by each of the CNs in the $(j+1)$th time-slot can be derived as

$$Q_D[j+1] = \text{Pr}(\mathcal{H}_1|\mathcal{H}_1) = \prod_{k=1}^{K} \text{Pr}(\mathcal{H}_{1,k}^{\text{FC}}|\mathcal{H}_1), \tag{5}$$

$$Q_F[j+1] = \text{Pr}(\mathcal{H}_1|\mathcal{H}_0) = \prod_{k=1}^{K} \text{Pr}(\mathcal{H}_{1,k}^{\text{FC}}|\mathcal{H}_0), \tag{6}$$

where $\text{Pr}(\mathcal{H}_{1,k}^{\text{FC}}|\mathcal{H}_1)$ and $\text{Pr}(\mathcal{H}_{1,k}^{\text{FC}}|\mathcal{H}_0)$ can be derived as

$$\begin{aligned}&\text{Pr}(\mathcal{H}_{1,k}^{\text{FC}}|\mathcal{H}_1)\\ &= \text{Pr}(\mathcal{H}_{1,k}^{\text{FC}}|\mathcal{H}_{0,k}^{\text{CN}})\text{Pr}(\mathcal{H}_{0,k}^{\text{CN}}|\mathcal{H}_1) + \text{Pr}(\mathcal{H}_{1,k}^{\text{FC}}|\mathcal{H}_{1,k}^{\text{CN}})\text{Pr}(\mathcal{H}_{1,k}^{\text{CN}}|\mathcal{H}_1)\\ &= P_{F,k}^{\text{FC}}[j+1](1-P_{D,k}^{\text{CN}}) + P_{D,k}^{\text{FC}}[j+1]P_{D,k}^{\text{CN}},\end{aligned} \tag{7}$$

$$\begin{aligned}&\text{Pr}(\mathcal{H}_{1,k}^{\text{FC}}|\mathcal{H}_0)\\ &= \text{Pr}(\mathcal{H}_{1,k}^{\text{FC}}|\mathcal{H}_{0,k}^{\text{CN}})\text{Pr}(\mathcal{H}_{0,k}^{\text{CN}}|\mathcal{H}_0) + \text{Pr}(\mathcal{H}_{1,k}^{\text{FC}}|\mathcal{H}_{1,k}^{\text{CN}})\text{Pr}(\mathcal{H}_{1,k}^{\text{CN}}|\mathcal{H}_0)\\ &= P_{F,k}^{\text{FC}}[j+1](1-P_{F,k}^{\text{CN}}) + P_{D,k}^{\text{FC}}[j+1]P_{F,k}^{\text{CN}},\end{aligned} \tag{8}$$

where $P_{D,k}^{\text{FC}}[j+1]$ and $P_{F,k}^{\text{FC}}[j+1]$ denote the probabilities of detection and false alarm at the FC corresponding to the transmission by the kth CN in the $(j+1)$th time-slot.

[6]This approximation is reasonable when $n_k q_k^0 > 5$ and $n_k(1-q_k^0) > 5$ [32], [33], [40]. It is also worth mentioning that this Gaussian assumption is also applicable under mobile kth CN and mobile FC scenario assuming the number of molecules n_k released by the kth CN to be sufficiently large.

2) OR Rule: The probabilities of detection $Q_D[j+1]$ and false alarm $Q_F[j+1]$ at FC can be derived as

$$Q_D[j+1] = \text{Pr}(\mathcal{H}_1|\mathcal{H}_1) = 1 - \prod_{k=1}^{K} \text{Pr}(\mathcal{H}_{0,k}^{\text{FC}}|\mathcal{H}_1), \tag{9}$$

$$Q_F[j+1] = \text{Pr}(\mathcal{H}_1|\mathcal{H}_0) = 1 - \prod_{k=1}^{K} \text{Pr}(\mathcal{H}_{0,k}^{\text{FC}}|\mathcal{H}_0), \tag{10}$$

where $\text{Pr}(\mathcal{H}_{0,k}^{\text{FC}}|\mathcal{H}_1)$ and $\text{Pr}(\mathcal{H}_{0,k}^{\text{FC}}|\mathcal{H}_0)$ are given as

$$\begin{aligned}&\text{Pr}(\mathcal{H}_{0,k}^{\text{FC}}|\mathcal{H}_1)\\ &= \text{Pr}(\mathcal{H}_{0,k}^{\text{FC}}|\mathcal{H}_{0,k}^{\text{CN}})\text{Pr}(\mathcal{H}_{0,k}^{\text{CN}}|\mathcal{H}_1) + \text{Pr}(\mathcal{H}_{0,k}^{\text{FC}}|\mathcal{H}_{1,k}^{\text{CN}})\text{Pr}(\mathcal{H}_{1,k}^{\text{CN}}|\mathcal{H}_1)\\ &= (1-P_{F,k}^{\text{FC}}[j+1])(1-P_{D,k}^{\text{CN}}) + (1-P_{D,k}^{\text{FC}}[j+1])P_{D,k}^{\text{CN}},\end{aligned} \tag{11}$$

$$\begin{aligned}&\text{Pr}(\mathcal{H}_{0,k}^{\text{FC}}|\mathcal{H}_0)\\ &= \text{Pr}(\mathcal{H}_{0,k}^{\text{FC}}|\mathcal{H}_{0,k}^{\text{CN}})\text{Pr}(\mathcal{H}_{0,k}^{\text{CN}}|\mathcal{H}_0) + \text{Pr}(\mathcal{H}_{0,k}^{\text{FC}}|\mathcal{H}_{1,k}^{\text{CN}})\text{Pr}(\mathcal{H}_{1,k}^{\text{CN}}|\mathcal{H}_0)\\ &= (1-P_{F,k}^{\text{FC}}[j+1])(1-P_{F,k}^{\text{CN}}) + (1-P_{D,k}^{\text{FC}}[j+1])P_{F,k}^{\text{CN}}.\end{aligned} \tag{12}$$

Now, the closed-form expressions for $P_{F,k}^{\text{FC}}[j+1]$ and $P_{D,k}^{\text{FC}}[j+1]$ can be obtained by formulating the binary hypothesis testing problem using (1) as

$$\begin{aligned}\mathcal{H}_{0,k}^{\text{FC}}&:\widetilde{R}_k[j+1]{=}\widetilde{\mathcal{I}}_k[j+1]{+}\widetilde{N}_k[j+1]{+}\widetilde{C}_k[j+1]\\ \mathcal{H}_{1,k}^{\text{FC}}&:\widetilde{R}_k[j+1]{=}\widetilde{S}_k[j+1]{+}\widetilde{\mathcal{I}}_k[j+1]{+}\widetilde{N}_k[j+1]{+}\widetilde{C}_k[j+1].\end{aligned} \tag{13}$$

In (13), the number of molecules $\widetilde{R}_k[j+1]$ corresponds to the null and alternative hypotheses following a Gaussian distribution as

$$\begin{aligned}\mathcal{H}_{0,k}^{\text{FC}} &: \widetilde{R}_k[j+1] \sim \mathcal{N}(\widetilde{\mu}_{k,0}[j+1], \widetilde{\sigma}_{k,0}^2[j+1])\\ \mathcal{H}_{1,k}^{\text{FC}} &: \widetilde{R}_k[j+1] \sim \mathcal{N}(\widetilde{\mu}_{k,1}[j+1], \widetilde{\sigma}_{k,1}^2[j+1]),\end{aligned} \tag{14}$$

where the mean $\widetilde{\mu}_{k,0}[j+1]$ and the variance $\widetilde{\sigma}_{k,0}^2[j+1]$ under the null hypothesis $\mathcal{H}_{0,k}^{\text{FC}}$ are calculated as

$$\widetilde{\mu}_{k,0}[j+1] = \sum_{i=2}^{j} \beta_k n_k q_k^{i-1} + \mu_o, \tag{15}$$

$$\begin{aligned}\widetilde{\sigma}_{k,0}^2[j+1] = \sum_{i=2}^{j} \big\{&\beta_k n_k q_k^{i-1}(1-q_k^{i-1}) + \beta_k(1-\beta_k)\\ &\times (n_k q_k^{i-1})^2\big\} + \sigma_o^2 + \widetilde{\mu}_{k,0}[j+1],\end{aligned} \tag{16}$$

and the probability β_k is given as $\beta_k{=}\text{Pr}(x_k[j-i+1]{=}1|\mathcal{H}_1)\text{Pr}(\mathcal{H}_1){+}\text{Pr}(x_k[j-i+1]{=}1|\mathcal{H}_0)\text{Pr}(\mathcal{H}_0){=}P_{D,k}^{\text{CN}}\beta{+}P_{F,k}^{\text{CN}}(1{-}\beta)$, where β denotes the probability of occurrence of the abnormality. Similarly, mean $\widetilde{\mu}_{k,1}[j{+}1]$, variance $\widetilde{\sigma}_{k,1}^2[j{+}1]$ under the alternative hypothesis $\mathcal{H}_{1,k}^{\text{FC}}$ are derived as[7]

$$\widetilde{\mu}_{k,1}[j+1] = n_k q_k^0 + \widetilde{\mu}_{k,0}[j+1], \tag{17}$$

$$\widetilde{\sigma}_{k,1}^2[j+1] = n_k q_k^0(2-q_k^0) + \widetilde{\sigma}_{k,0}^2[j+1]. \tag{18}$$

Employing the above results in the likelihood ratio test (LRT), the test at the FC corresponding to the transmission by the kth CN can be seen as [26, Theorem 1]

$$T(\widetilde{R}_k[j+1]) = \widetilde{R}_k[j+1] \underset{\mathcal{H}_{0,k}^{\text{FC}}}{\overset{\mathcal{H}_{1,k}^{\text{FC}}}{\gtrless}} \gamma_k'[j+1], \tag{19}$$

[7]It is worth noting that deriving the exact optimal LRT detector is computationally cumbersome [17], as it involves computing the likelihoods of all the possible combinations of previously sent symbols conditioned over the two hypotheses. Therefore, similar to [33], [41], this work obtains sub-optimal detectors where the mean and the variance under null and alternative hypotheses are given in terms of average number of interfering molecules.

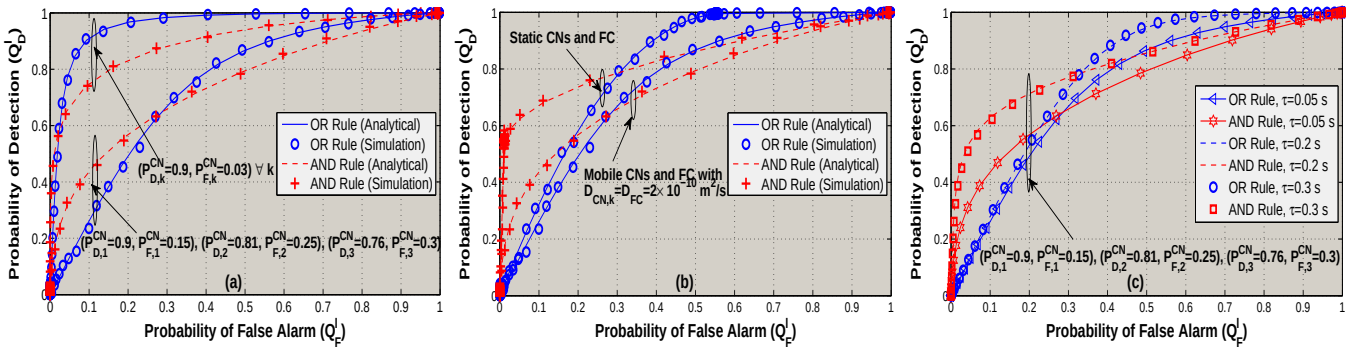

Fig. 1: Detection performance at the FC employing OR and AND fusion rules with (a) different detection performance at the CNs with slot duration $\tau = 0.05$ s, (b) different mobility conditions with $\tau = 0.05$ s and the detection performance at the CNs as $(P_{D,1}^{\text{CN}} = 0.9, P_{F,1}^{\text{CN}} = 0.15)$, $(P_{D,2}^{\text{CN}} = 0.81, P_{F,2}^{\text{CN}} = 0.25)$, $(P_{D,3}^{\text{CN}} = 0.76, P_{F,3}^{\text{CN}} = 0.30)$, and (c) different values of τ.

where the decision threshold $\gamma_k'[j+1]$ is given as

$$\gamma_k'[j+1] = \sqrt{\gamma_k[j+1]} - \alpha_k[j+1]. \tag{20}$$

In (20), the quantities $\gamma_k[j+1]$ and $\alpha_k[j+1]$ are defined as

$$\alpha_k[j+1] = \frac{\widetilde{\mu}_{k,1}[j+1]\widetilde{\sigma}^2_{k,0}[j+1] - \widetilde{\mu}_{k,0}[j+1]\widetilde{\sigma}^2_{k,1}[j+1]}{\widetilde{\sigma}^2_{k,1}[j+1] - \widetilde{\sigma}^2_{k,0}[j+1]},$$

$$\gamma_k[j+1] = \frac{2\widetilde{\sigma}^2_{k,1}[j+1]\widetilde{\sigma}^2_{k,0}[j+1]}{\widetilde{\sigma}^2_{k,1}[j+1] - \widetilde{\sigma}^2_{k,0}[j+1]} \ln\left[\frac{(1-\beta_k)\widetilde{\sigma}_{k,1}[j+1]}{\beta_k \widetilde{\sigma}_{k,0}[j+1]}\right]$$
$$+(\alpha_k[j+1])^2 + \frac{\widetilde{\mu}^2_{k,1}[j+1]\widetilde{\sigma}^2_{k,0}[j+1] - \widetilde{\mu}^2_{k,0}[j+1]\widetilde{\sigma}^2_{k,1}[j+1]}{\widetilde{\sigma}^2_{k,1}[j+1] - \widetilde{\sigma}^2_{k,0}[j+1]}.$$

Now, using the above test, the expressions for the $P_{D,k}^{\text{FC}}[j+1]$ and $P_{F,k}^{\text{FC}}[j+1]$ can be obtained as

$$P_{D,k}^{\text{FC}}[j+1] = Q\left(\frac{\gamma_k'[j+1] - \widetilde{\mu}_{k,1}[j+1]}{\widetilde{\sigma}_{k,1}[j+1]}\right), \tag{21}$$

$$P_{F,k}^{\text{FC}}[j+1] = Q\left(\frac{\gamma_k'[j+1] - \widetilde{\mu}_{k,0}[j+1]}{\widetilde{\sigma}_{k,0}[j+1]}\right). \tag{22}$$

IV. Simulation Results and Conclusion

For simulation purposes, the abnormality is considered to occur with probability $\beta = 0.2$ and the various parameters are set as in [33]: the diffusion coefficient $D_{\text{P}} = 242.78 \times 10^{-12}$ m^2/s, the number of slots l=10, the number of CNs K=3 with distances $d_{0,1} = 20$ μm, $d_{0,2} = 15$ μm, $d_{0,3} = 10$ μm from the FC at $\tau = 0$, the number of molecules transmitted $n_k = 100$ for $x_k[j] = 1$ $\forall j$, and each CN and FC are assumed to be mobile with diffusion coefficients $D_{\text{CN},k} = D_{\text{FC}} = 2\times10^{-10}$ m^2/s under flow-induced diffusive channel with drift velocity $v = 3\times10^{-3}$ m/s. Moreover, the detection performance at the CNs is as shown in Fig. 1 where $P_{D,k}^{\text{CN}}[j] = P_{D,k}^{\text{CN}}$, $P_{F,k}^{\text{CN}}[j] = P_{F,k}^{\text{CN}}, \forall j$ and the MSI at the FC is modeled as a Gaussian distributed RV with mean $\mu_o = 10$ and variance $\sigma_o^2 = 10$.

Fig. 1a demonstrates the detection performance at the mobile FC considering different detection performances at the mobile CNs. First, it can be observed from Fig. 1a that the analytical values derived in (4) match exactly with the simulation results, thereby validating the derived analytical results. Further, the detection performance at the FC heavily depends on the detection performance of the CNs. The detection performance at the mobile FC significantly improves with the improvement in the detection performance of mobile CNs. One can also observe that at low values of the probability of false alarm (Q_F^l), the AND fusion rule outperforms the OR rule. However, as the value of Q_F^l increases, significant increase in performance gain of the OR rule can be observed over the AND rule. For low Q_F^l, it is intuitive that the probability of detection (Q_D^l) for the AND rule will be better than the OR rule because the AND rule decides $\mathcal{H}_1$ only when all the mobile CNs say $\mathcal{H}_1$. However, for higher values of Q_F^l, i.e., each mobile CN is likely to be in error, the increase in the Q_D^l for the AND rule will be more than the OR rule.

Fig. 1b shows the impact of mobility on the detection performance at the FC employing both OR and AND fusion rules, where $D_{\text{CN},k}, D_{\text{FC}}$ are zero for fixed CNs and FC as considered in [1, Fig. 2d]. It can be seen that in comparison to the fixed or static case, the detection performances at the FC under OR and AND rules significantly degrade for the scenario when each CNs and FC are mobile in a flow-induced diffusive medium with $v = 3 \times 10^{-3}$ m/s. This is due to the fact that the probability of a molecule reaching the FC within the current slot, i.e., q_k^0 progressively decreases while the ISI from previous slots increases as $D_{\text{CN},k}, D_{\text{FC}}$ increase due to mobility. It is also important to note that the crossover point, after which the OR fusion rule performs better than the AND rule, decreases from $(Q_D^l = 0.79, Q_F^l = 0.3)$ to $(Q_D^l = 0.64, Q_F^l = 0.27)$ with the increase in $D_{\text{CN},k}$ and D_{FC}.

Fig. 1c illustrates the detection performance at the FC for different values of slot duration (τ), where each CN and FC are mobile with diffusion coefficient 2×10^{-10} m^2/s. It is shown that the detection performance at the mobile FC considering OR and AND fusion rules improves as τ increases from 0.05 s to 0.2 ms. However, the detection performance at the mobile FC saturates for further increase in τ. This is due to the fact that the performance at the mobile FC is dominated by the detection performance of the mobile CNs. Additional simulation results can be seen in [42].

Conclusion: This work analyzed the performance of cooperative abnormality detection with multiple CNs and a FC employing OR/ AND fusion rules, where each CN reports its local decision to the FC over a flow-induced diffusive channel with ISI, MSI and counting errors. Future studies can focus on dependent observations at the CNs as well as on modeling of the CN to FC link in 3-dimensional (3-D) scenarios.

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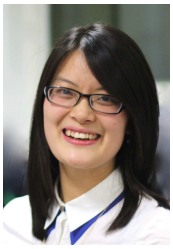

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