Analysis of Quality of Surveillance in Fusion-based Sensor Networks

Rui Tan* Guoliang Xing† Xunteng Xu* Jianping Wang*
*Department of Computer Science, City University of Hong Kong, HKSAR
†Department of Computer Science and Engineering, Michigan State University, USA
tanrui2@student.cityu.edu.hk; glxing@msu.edu; xuntengxu2@student.cityu.edu.hk; jianwang@cityu.edu.hk

***Abstract*—Recent years have witnessed the deployments of wireless sensor networks for mission-critical applications such as battlefield monitoring and security surveillance. These applications often impose stringent Quality of Surveillance (QoSv) requirements including low false alarm rate and short detection delay. In practice, collaborative data fusion techniques that can deal with sensing uncertainty and enable sensor collaboration have been widely employed in sensor systems to achieve stringent QoSv requirements. However, most previous analytical studies on the surveillance performance of wireless sensor networks are based on simplistic models (such as the disc model) that cannot capture the stochastic and collaborative nature of sensing. In this paper, we systematically analyze the fundamental relationship between QoSv, network density, sensing parameters, and target properties. The results show that data fusion is effective in achieving stringent QoSv requirements, especially in the senarios with low signal-to-noise ratios (SNRs). In contrast, the disc model is only suitable when the SNR is sufficiently high. Our results help understand the limitations of disc model and provide insights into improving QoSv of sensor networks using data fusion.**

I. INTRODUCTION

Wireless sensor networks (WSNs) are increasingly deployed for mission-critical applications such as battlefield monitoring and security surveillance. A fundamental challenge for these WSNs is to meet the stringent Quality of Surveillance (QoSv) requirements such as low false alarm rate, high target detection probability and short detection delay. In particular, low-power sensors only have limited sensing capabilities. For instance, the false alarm rate of a single acoustic sensor may be as high as 60% [1]. Moreover, many surveillance applications must ensure QoSv over a vast geographic region, which hence require sensors to efficiently collaborate with each other.

In practice, collaborative signal processing techniques such as data fusion [2] are widely employed by current sensor systems [1], [3]. These techniques can improve the QoSv of WSNs by enabling the cooperation among multiple sensors with limited capability. However, performance analysis of QoSv in fusion-based sensor networks is extremely challenging due to the stochastic nature of data fusion algorithms. Most previous analytical studies are based on overly simplistic sensing models, such as the disc model [4]–[7]. In the disc model, a sensor *deterministically* detects the targets within a circular region centered at the sensor. Although such a model allows a geometric treatment in analyzing the QoSv of WSNs, a key shortcoming is that it fails to capture the stochastic nature of sensing, such as the probabilistic detectability caused by noise. Moreover, most studies based on the disc model do not exploit the collaboration among sensors.

In our previous work [8], we developed an analytical framework to study the QoSv of large-scale WSNs that adopt collaborative data fusion algorithms. To quantify the fundamental trade-off between detection delay and false alarm rate, we proposed a new QoSv metric called α-delay that is defined as the average delay of detecting mobile targets subject to the false alarm rate bound α. In this paper, we significantly extend our previous study in several important aspects. First, unlike most existing analytical studies [3], [8] that adopt a specific target signal decay model, we assume a general power-law decay model that can characterize the attenuation of many physical signals, *e.g.*, acoustic and electromagnetic signals. Second, we aim to extend our analysis to the case of arbitrary target speed, which is in contrast to [8] where target speed is assumed to be very high. Due to the arbitrary target speed, successive data fusion processes may be statistically *correlated* because of the sharing of common sensors. Such correlation among data fusion processes substantially complicates the analysis of QoSv. The main contributions of this paper include:

- We present new analytical results on the QoSv of fusion-based sensor networks for intrusion detection. The results can be used to achieve desirable trade-offs between false alarm rate, detection delay and network density.
- To understand the limitation of the disc model and the impact of data fusion on the QoSv of WSNs, we conduct comparative analysis between the two models. In particular, we show that the ratio of network densities to achieve the minimum α-delay under the two models has an asymptotic upper bound of $\mathcal{O}\left(\left(\frac{\text{SNR}}{Q^{-1}(\alpha)}\right)^{2/k}\right)$, where k is the signal path loss exponent and $Q^{-1}(\cdot)$ is the inverse of the complementary cumulative distribution function of the standard normal distribution. The result implies that data fusion is effective in achieving stringent QoSv requirements, especially in the scenarios with low signal-to-noise ratios (SNRs). In contrast, the disc model is suitable only when the SNR is sufficiently high.
- We conduct extensive simulations under realistic settings to verify our theoretical study. The results show that the data fusion model is more robust than the disc model in detecting slowly moving targets.

The rest of this paper is organized as follows. Section II reviews related work. Section III introduces the preliminaries and problem definition. In Section IV, we derive the α-delay under the disc and fusion models, respectively. In Section V, we study the impact of data fusion through performance comparison between the two models. Section VI presents simulation results and Section VII concludes this paper.

II. RELATED WORK

Many sensor network systems have incorporated various data fusion schemes to improve the system performance [1],

[9], [10]. In the surveillance system based on MICA2 motes developed in [1], the system false alarm rate is reduced by fusing the detection decisions made by multiple neighboring sensors. In the DARPA SensIT project, advanced data fusion techniques have been employed in a number of algorithms designed for target detection, localization and classification [3], [9], [10]. The routing algorithms that jointly account for communication and data fusion costs have been studied in [11], [12]. In our recent work, we have developed static sensor deployment algorithms [13] and mobile sensor scheduling algorithms [14], [15] for fusion-based target detection in WSNs. However, the performance analysis of large-scale fusion-based WSNs has received little attention.

Most existing analytical studies on target detection [5]–[7] in WSNs are based on the simplistic disc model. The delay of detecting mobile targets with randomly deployed sensors has been analyzed in [5], [6]. The length of free path that a target travels undetected is derived in [7]. However, the disc model adopted by these works fails to capture the stochastic characteristics of real-world surveillance applications, such as probabilistic detectability and false alarms. In our previous works [8], [16], we proposed a probabilistic disc model that extends the existing analytical results based on the classical disc model to the context of stochastic detection. Moreover, we studied the impact of data fusion on sensing coverage [16] and detection delay [8] by comparing the system performance under the disc and fusion models. However, in [8], we assumed a particular signal decay model and high target speed. In this paper, we extend our study to the general cases of signal decay and target speed.

III. Preliminaries and Problem Definition

In this section, we first describe the preliminaries of our work, which include sensor measurement, network, and data fusion models. We then introduce the problem definition.

A. Sensor Measurement and Network Models

Sensors perform detection by measuring the energy of signals emitted by the target. The energy of most physical signals (*e.g.*, acoustic and electromagnetic signals) attenuates with the distance from the signal source. Suppose sensor i is d_i meters away from the target that emits a signal of energy S. The attenuated signal energy s_i at the position of sensor i is given by $s_i = S \cdot w(d_i)$, where $w(\cdot)$ is a decreasing function satisfying $w(0) = 1$, $w(\infty) = 0$, and $w(x) = \Theta(x^{-k})$.[1] Depending on the environment, k typically ranges from 2.0 to 5.0. We note that the theoretical results derived in this paper do not depend on the closed-form formula of $w(\cdot)$. We adopt $w(x) = \frac{1}{1+x^k}$ in the simulations conducted in this paper, and we set $k = 2$ except those explicitly specified. The measurements of sensors are contaminated by additive random noises from sensor hardware or environment. Depending on the hypothesis that the target is absent (H_0) or present (H_1), the measurement of sensor i, denoted by y_i, is given by $y_i|H_0 = n_i$ and $y_i|H_1 = s_i + n_i$, where n_i is the energy of noise experienced by sensor i. We assume that the noise n_i at each sensor i follows the normal distribution, *i.e.*, $n_i \sim \mathcal{N}(\mu, \sigma^2)$, where μ and σ^2 are the mean and variance of n_i, respectively. Moreover, we assume that $\{n_i|\forall i\}$ are spatially independent across sensors. We define the SNR as $\delta = S/\sigma$ which quantifies the noise level. The above signal decay and sensor measurement models have been widely assumed in the literature of signal detection [2] and also have been empirically verified [10].

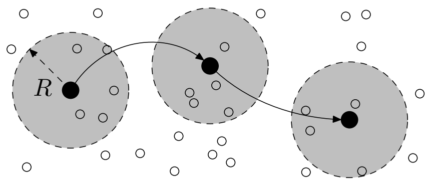
We assume that a sensor executes detection task every T seconds, where T is referred to as the *detection period*. In each detection period, a sensor gathers the signal energy during the *sampling interval* for the detection made in the current period. We note that such an intermittent measurement scheme is consistent with several wireless sensor systems for target detection and tracking [1], [3]. For instance, a sensor may wake up every 5 seconds and sample acoustic energy for 0.05 seconds, where T is 5 s and the sampling interval is 0.05 s [3], [10]. We assume that the sampling interval is much shorter than the detection period.

We consider a network deployed in a vast two-dimensional geographical region. We assume that the positions of sensors are uniformly and independently distributed in the deployment region. Such a deployment scenario can be modeled as a stationary two-dimensional Poisson point process. Let ρ denote the density of the underlying Poisson point process. We assume that the target may appear at any location in the deployment region and move freely. Moreover, the target is blind to the network, *i.e.*, the target does not know the sensors' positions, and hence it cannot choose a moving scheme to reduce the probability of being detected. The sensors synchronously detect the target, and we refer to the target detection in one detection period as the *unit detection*. The process of detecting a target consists of a series of unit detections. As the sampling interval is much shorter than the detection period, we ignore the target's movement during the sampling interval.

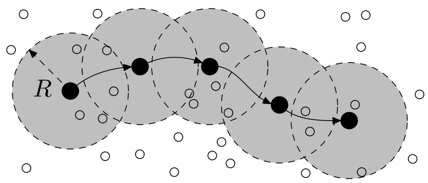
B. Data Fusion Model

Data fusion [2] can improve the performance of detection systems by jointly considering the noisy measurements of multiple sensors. We adopt a data fusion scheme as follows. For any physical point P, the sensors within a distance of R meters from P participate in the data fusion to detect whether a target is present at P, where R is referred to as the *fusion range*. The number of sensors within the fusion range of P is represented by $N(P)$. For conciseness, we use N for $N(P)$ when the point of interest is clear. Due to the Poisson process deployment, for a random point P, N follows the Poisson distribution with mean of $\rho\pi R^2$, *i.e.*, $N \sim \mathrm{Poi}(\rho\pi R^2)$. In each detection period, a cluster head is elected to make the detection decision by comparing the sum of measurements reported by member sensors within the fusion range against a detection threshold η. Let Y denote the sum of measurements, *i.e.*, $Y = \sum_{i=1}^{N} y_i$. If $Y \geq \eta$, the cluster head decides H_1; otherwise,

[1]We adopt the following asymptotic notation: 1) $f(x) = \Theta(g(x))$ means that $g(x)$ is the asymptotic tight bound of $f(x)$; 2) $f(x) = \mathcal{O}(g(x))$ means that $g(x)$ is the asymptotic upper bound of $f(x)$.



(a) No-overlap case



(b) Overlap case

Figure 1. Intrusion detection under the data fusion model. The void circles represent sensors; the solid circles represent the target in different sampling intervals, and a unit detection is performed in each sampling interval; the dashed discs represent the fusion ranges. The figure shows two cases: (a) In the *no-overlap* case, there is no overlap between any two fusion ranges; (b) In the *overlap* case, the fusion ranges can overlap.

it decides H_0. Fig. 1 illustrates the intrusion detection under the fusion model.

We assume that the system can obtain the position of a possible target through a localization service in the network [10]. Our previous analysis [8] based on a simple localization algorithm shows that the localization error decreases with network density and becomes insignificant when the network density is high enough. Therefore, the localization error can be safely ignored in our analysis that is focused on the detection delay when the network density is high. In each detection period, a cluster is formed by the sensors within the fusion range centered at the possible target to make a detection decision. The cluster formation may be initiated by the sensor that has the maximum measurement. Such a scheme can be implemented by several dynamic clustering algorithms [17].

C. Problem Definition

The delay of detecting mobile targets is an important QoSv metric of surveillance WSNs. As the process of detecting a target is inherently stochastic, detection delay is closely related to two system performance metrics, namely, the false alarm rate (denoted by P_F) and detection probability (denoted by P_D). P_F is the probability of making a positive decision when no target is present, and P_D is the probability that a present target is correctly detected. Although detection delay can be reduced by making sensors more sensitive (*e.g.*, setting lower detection thresholds), the fidelity of detection results may be unacceptable because of high false alarm rates caused by noises. To quantify the trade-off between detection delay and false alarm rate, we proposed a new QoSv metric called α-delay in [8], which is stated as follows.

Definition 1 ([8]). α-delay is the average number of detection periods before a target is first detected subject to that the false alarm rate of the network is no greater than α, *i.e.*, $P_F \le \alpha$, where $\alpha \in (0, 1)$.

In [8], we derived the relationship between the α-delay and network density. Moreover, we investigated the impact of data fusion on the QoSv by comparing the network densities under the disc and fusion models for achieving the same α-delay. However, our analyses in [8] have two major limitations. First, it is assumed that the signal emitted by the target follows the Inverse-square law, which is a specific case of the signal decay model in Section III-A with $k = 2$. However, the Inverse-square law is only applicable to the attenuation of acoustic and seismic signals in open space. Second, it is assumed that there is no overlap between any two fusion ranges, which is referred to as the *no-overlap* case and illustrated in Fig. 1(a). The no-overlap condition may not be satisfied if the target speed is low or the detection period T is short. In this paper, we will generalize the analyses in [8] to the significantly more general power-law decay model and the *overlap* case of data fusion as illustrated in Fig. 1(b). In addition, we will investigate the impact of target speed on the QoSv of a network.

IV. α-Delay under Probabilistic Disc and Data Fusion Models

In this section, we derive the α-delay under the probabilistic disc model [8], [16] and data fusion model, respectively. The results will be used to study the impact of data fusion on the QoSv of WSNs in Section V.

A. α-Delay under Probabilistic Disc Model

In our previous works [8], [16], we extended the classical disc model to capture the probabilistic sensing characteristics. The *probabilistic disc model* lays a foundation for understanding the limitation of disc model on quantifying the QoSv of WSNs. Let $Q(\cdot)$ denote the complementary cumulative distribution function (CDF) of the standard normal distribution, *i.e.*, $Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty \mathrm{e}^{-t^2/2} \mathrm{d}t$. In the probabilistic disc model, the sensing range of a sensor, denoted by r, is given by [16]:

$$r = w^{-1}\left(\frac{Q^{-1}(\alpha) - Q^{-1}(\beta)}{\delta}\right), \qquad (1)$$

where α and β are two constants within $(0, 1)$, $w^{-1}(\cdot)$ and $Q^{-1}(\cdot)$ are the inverse functions of $w(\cdot)$ and $Q(\cdot)$, respectively. Under such a model, the probability of detecting any target within the sensing range of a sensor is no lower than β and the false alarm rate is no greater than α. With this model, the existing analytical results based on the classical model [5]–[7] can be extended to the context of stochastic detection.

We now derive the α-delay under the probabilistic disc model. We refer to the circular region with radius of r centered at the target as the *target disc*. In each unit detection, if there is at least one sensor within the target disc, the target can be detected with a probability of no lower than β. By letting β be sufficiently close to 1 (*e.g.*, $\beta = 0.99$), sensors can exhibit the deterministic detectability as under the classical disc model. In our previous work [8], we proved that the α-delay under the probabilistic disc model is $\tau = 1/(1 - \mathrm{e}^{-\rho\pi r^2})$ if there is no overlap between any two target discs. However, the no-overlap condition may not hold if the target speed is low or the detection period T is short. For instance, suppose the target moves at a constant speed of v, the no-overlap condition cannot be satisfied if $vT < 2r$. In this section, we derive the α-delay without the no-overlap condition, which is given by the following lemma (the proof is omitted due to space limit and can be found in [18]).

Lemma 1. *Let τ denote the α-delay under the probabilistic disc model. We have $\tau \geq \frac{1}{1-\mathrm{e}^{-\rho\pi r^2}}$, where r is given by (1).*

Compared with the result in [8], we can see from Lemma 1 that the α-delay is minimized for the no-overlap case. Intuitively, the area covered by the union of target discs is maximized in the no-overlap case, which yields the maximum overall detection probability for a given number of detection periods and in turn leads to the minimum detection delay.

B. α-Delay under Data Fusion Model

Although the probabilistic disc model discussed in Section IV-A captures the stochastic nature of sensing, it does not exploit the possible collaboration among sensors. In this section, we derive α-delay under the data fusion model.

We first review the system detection performance in a unit detection derived in [8]. The results will be used to analyze the α-delay under the fusion model. It has been shown in [8], by setting the detection threshold of the fusion model as $\eta = N_j\mu + \sqrt{N_j}\sigma Q^{-1}(\alpha)$ where N_j is the number of sensors within the fusion range in the j^{th} unit detection, the system false alarm rate is α and the detection probability is

$$P_{Dj} = Q\left(\frac{\sigma}{\sqrt{\sigma_s^2+\sigma^2}} \cdot Q^{-1}(\alpha) - \frac{\mu_s}{\sqrt{\sigma_s^2+\sigma^2}} \cdot \sqrt{N_j}\right), \quad (2)$$

where μ_s and σ_s^2 are the mean and variance of the signal energy received by any sensor in fusion range. The formulae for μ_s and σ_s^2 have been derived in [8], [16], *i.e.*, $\mu_s = \frac{2S}{R^2}\int_0^R w(d_i)d_i\mathrm{d}d_i$ and $\sigma_s^2 = \frac{2S^2}{R^2}\int_0^R w^2(d_i)d_i\mathrm{d}d_i - \mu_s^2$.

As discussed in Section III-A, the process of detecting a target consists of a series of unit detections. In [8], we proved that the α-delay under the fusion model is $\tau = 1/\mathbb{E}[P_D]$ if there is no overlap between any two fusion ranges. However, the no-overlap condition may not hold if the target speed is low or the detection period T is short. For instance, suppose the target moves at a constant speed of v, the no-overlap condition cannot be satisfied if $vT < 2R$. In this section, we derive the α-delay without the no-overlap condition, which is given by the following theorem (the proof is omitted due to space limit and can be found in [18]).

Theorem 1. *Let τ denote the α-delay of fusion-based detection. We have $\tau \leq \mathbb{E}[1/P_D]$, where P_D is the detection probability in any unit detection.*

As $1/P_D$ is a convex function of P_D, according to Jensen's inequality, $\mathbb{E}[1/P_D] \geq 1/\mathbb{E}[P_D]$, where $1/\mathbb{E}[P_D]$ is the α-delay under the no-overlap case. We now discuss how to compute $\mathbb{E}[1/P_D]$ in Theorem 1. As P_{Dj} is a function of N_j which follows the Poisson distribution, *i.e.*, $N_j \sim \mathrm{Poi}(\rho\pi R^2)$, $\mathbb{E}[1/P_D]$ can be numerically computed by averaging $\frac{1}{P_{Dj}}$ over the distribution of N_j.

V. Impact of Data Fusion on Quality of Surveillance

Many mission-critical surveillance applications require detection delay to be as small as possible [1], [19]. As an asymptotic case, the α-delay approaches one, *i.e.*, any intruder can be detected almost surely in the first detection period after its appearance, which is referred to as the *instant detection*. As a smaller detection delay always requires more sensors, the network density for achieving instant detection is an important cost metric for mission-critical surveillance WSNs. In this section, we study the ratio of network densities required by the disc and fusion models for achieving instant detection, which characterizes the relative cost of the two models when detection delay is minimized. The result provides important insights into understanding the limitation of disc model and the impact of data fusion on the QoSv of surveillance WSNs.

A. Network Density for Achieving Instant Detection

In our previous work [8], we have obtained the ratio of network densities for instant detection when the target signal follows the Inverse-square decay law (*i.e.*, $w(x) = \Theta(x^{-2})$) and the target discs and fusion ranges under the two models do not overlap. In this section, we derive the density ratio without the no-overlap conditions and extend the result to the general power-law decay model in Section III-A. We have the following theorem.

Theorem 2. *Let ρ_f and ρ_d denote the network densities for achieving α-delay of τ under the fusion and disc models, respectively. For given path loss exponent k, the ratio of network densities for instant detection satisfies*

$$\lim_{\tau\to 1^+} \frac{\rho_f}{\rho_d} = \mathcal{O}\left(\left(\frac{\delta}{Q^{-1}(\alpha)}\right)^{2/k}\right). \quad (3)$$

Proof: According to Lemma 1 and Theorem 1, we have

$$1/(1-\mathrm{e}^{-\rho_d\pi r^2}) \leq \tau \leq \mathbb{E}\left[1/P_D\right]. \quad (4)$$

We first find a upper bound of $\mathbb{E}[1/P_D]$. As we are not interested in the index of unit detection, we use N instead of N_j and P_D instead of P_{Dj}. As $\rho_f \to \infty$, $N \to \infty$ almost surely. In (2), the second item $-\frac{\mu_s}{\sqrt{\sigma_s^2+\sigma^2}} \cdot \sqrt{N}$ dominates when $\rho_f \to \infty$, since the first item $\frac{\sigma}{\sqrt{\sigma_s^2+\sigma^2}} \cdot Q^{-1}(\alpha)$ is a constant. Therefore, it is safe to use $P_D = Q(\gamma\sqrt{N})$ to approximate (2), where $\gamma = -\frac{\mu_s}{\sqrt{\sigma_s^2+\sigma^2}} < 0$. As $N \sim \mathrm{Poi}(\rho_f\pi R^2)$ and the Poisson distribution approaches to the normal distribution $\mathcal{N}(\rho_f\pi R^2, \rho_f\pi R^2)$ when $\rho_f \to \infty$, for any given constant $\xi \in (0,1)$, we have $\mathbb{P}(N \geq \xi\rho_f\pi R^2) = Q\left(\frac{\xi\rho_f\pi R^2 - \rho_f\pi R^2}{\sqrt{\rho_f\pi R^2}}\right) = Q\left((\xi-1)\sqrt{\rho_f\pi R^2}\right)$. When $\rho_f \to \infty$, $\mathbb{P}(N \geq \xi\rho_f\pi R^2) \to 1$, *i.e.*, $N \geq \xi\rho_f\pi R^2$ with high probability (*w.h.p.*). Moreover, as $1/P_D = 1/Q(\gamma N)$ is a decreasing function of N, $\mathbb{E}[1/P_D] \leq 1/Q(\gamma\sqrt{\xi\rho_f\pi R^2})$ *w.h.p.*. Furthermore, according to (4), we have $1/(1-\mathrm{e}^{-\rho_d\pi r^2}) \leq 1/Q(\gamma\sqrt{\xi\rho_f\pi R^2})$ *w.h.p.* when $\rho_f \to \infty$. After manipulation, we have $\rho_d \geq$

$-\frac{1}{\pi r^2}\ln\left(\Phi(\gamma\sqrt{\xi\pi}R\sqrt{\rho_f})\right)$, where $\Phi(x) = 1 - Q(x)$. Hence, we have

$$\lim_{\tau\to 1^+}\frac{\rho_f}{\rho_d} \le -\pi r^2 \lim_{\rho_f\to\infty}\frac{\rho_f}{\ln\left(\Phi(\gamma\sqrt{\xi\pi}R\sqrt{\rho_f})\right)} = \frac{2}{\gamma^2\xi R^2}\cdot r^2.$$

In the above derivation, we use the equality $\lim_{x\to\infty}\frac{x}{\ln\Phi(\vartheta\sqrt{x})} = -\frac{2}{\vartheta^2}$ (the proof can be found in [16]). Moreover, as γ is a constant when δ is fixed or approaches to infinity [8], we have $\lim_{\tau\to 1^+}\rho_f/\rho_d = \mathcal{O}(r^2)$. As $w^{-1}(x) = \Theta(x^{-1/k})$, according to (1), $r^2 = \Theta\left(\left(\frac{\delta}{Q^{-1}(\alpha)}\right)^{2/k}\right)$ for fixed β. Therefore, we have (3). ∎

Theorem 2 suggests that, for a certain path loss exponent k, the relative cost for instant detection between the fusion and disc models depends on the required false alarm rate α and SNR δ. First, when $\alpha \to 0$, $Q^{-1}(\alpha) \to \infty$ and hence $\lim_{\tau\to 1^+}\rho_f/\rho_d \to 0$. It suggests that data fusion can significantly reduce network density when a small false alarm rate is required. Second, the bound of density ratio increases with δ, which suggests that the advantage of data fusion diminishes as the SNR increases. Moreover, the path loss exponent k determines the order of density ratio with regard to the SNR. Intuitively, sensor collaboration is more advantageous when the SNR is low. However, when the SNR is *sufficiently* high, the detection performance of a single sensor is satisfactory and the collaboration among multiple sensors may be unnecessary.

B. Application of Results

In this section, we discuss the implications of Theorem 2 using numerical examples. As $\lim_{\tau\to 1^+}\rho_f/\rho_d \to 0$ when $\alpha \to 0$, if a small α is required, $\rho_f < \rho_d$ for instant detection, *i.e.*, the fusion model requires lower network density than the disc model. In other words, data fusion is effective in reducing detection delay and false alarms. Fig. 2 plots the upper bound of the density ratio versus the required false alarm rate under various SNRs. The fusion range R is set to be 25 m. From the figure, we can see that when SNR is lower than 19 dB, the fusion model outperforms the disc model as long as $\alpha < 0.2$. In practice, most mission-critical surveillance systems require a small α. For instance, in the vehicle detection system [1] and the acoustic shooter localization system [19], the false alarm rates are tuned to be near zero. Therefore, data fusion can significantly reduces the network density of these mission-critical surveillance systems.

Moreover, as $\lim_{\tau\to 1^+}\rho_f/\rho_d$ increases with δ for fixed α, if the SNR is high enough such that $\lim_{\tau\to 1^+}\rho_f/\rho_d > 1$, the disc model is superior to the fusion model in achieving instant detection. It implies that the disc model suffices when the SNR is sufficiently high. Fig. 3 plots the upper bound of density ratio versus SNR under various path loss exponents. From the figure, we can see linear and concave relationships between the density ratio and SNR when k is 2 and 4, respectively, which are consistent with Theorem 2. Moreover, if the SNR is sufficiently high (*e.g.*, 22 dB), the disc model outperforms the fusion model. However, the SNR depends on the characteristics of targets, environment and sensor device. For instance, the SNR can be extremely low when acoustic sensors experience strong wind. In the vehicle detection experiments based on low-power motes, *e.g.*, MICA2 [20] and ExScal [21], the SNRs are usually low to moderate (≤ 17 dB). In such a case, data fusion can effectively reduce the network density required to achieve short detection delay and low false alarm rate.

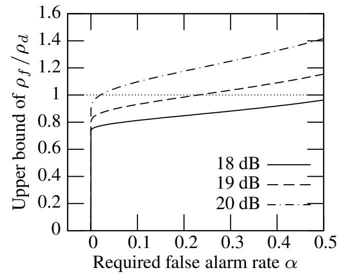


Figure 2. Upper bound of density ratio *vs.* required false alarm rate ($k = 2$).

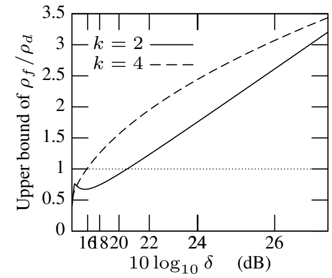


Figure 3. Upper bound of density ratio *vs.* SNR ($\alpha = 0.1\%$).

VI. Performance Evaluation

In this section, we conduct extensive simulations to evaluate the theoretical results in previous sections.

A. Simulation Settings and Methodology

In the simulations, sensors are deployed uniformly into a large field and periodically detect the target. The target moves in the deployment region with a constant speed. Under the fusion model, sensors within the fusion range of the target fuse their measurements and make the detection decision. Under the disc model, once the target enters the sensing range of a sensor, the sensor makes a detection. We conduct 500 runs with different random sensor deployments. The α-delay is computed as the average number of detection periods before the target is first detected in each run. We also evaluate the impact of the overlap/no-overlap condition by comparing the simulation results under the overlap and no-overlap cases. For the overlap case, the target moves $\frac{R}{2}$ and $\frac{r}{2}$ in each detection period under the fusion and disc models, respectively; for the no-overlap case, it moves $2R$ and $2r$, respectively.

B. Simulation Results

We first evaluate the analytical results on the α-delay under the two models. Fig. 4 plots the α-delay versus the network density under the fusion model. The curves labeled with "upper bound" and "analytical (no-overlap)" plot the upper bound of α-delay given by Theorem 1 and the analytical α-delay under the no-overlap case derived in [8], respectively. We can see that the two analytical results are very close. The other two curves plot the simulation results for the overlap and no-overlap cases, respectively. The simulation results confirm the analytical results when the network density is greater than 0.02. When ρ is smaller than 0.01, the simulations results start to deviate from the analytical results. This is due to the approximation made in the derivation of P_D. Moreover, we can see from Fig. 4 that the overlap/no-overlap condition has little impact on the α-delay under the fusion model. Fig. 5 plots the

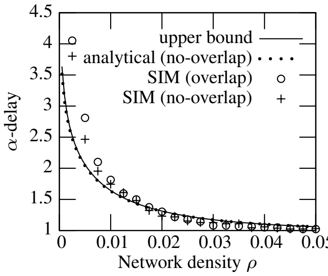


Figure 4. α-delay *vs.* network density under data fusion model.

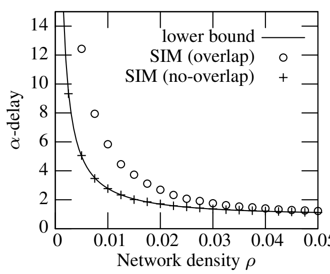


Figure 5. α-delay *vs.* network density under disc model.

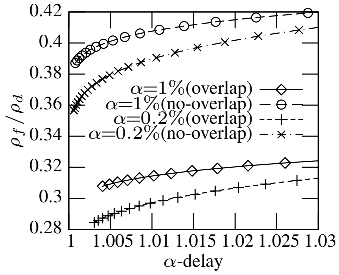


Figure 6. Density ratio *vs.* α-delay given different α (SNR $= 10\,\mathrm{dB}$).

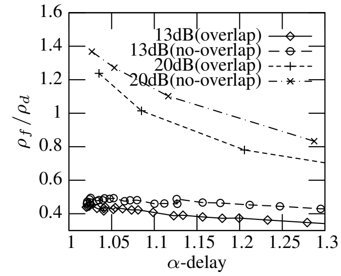


Figure 7. Density ratio *vs.* α-delay given different SNR ($\alpha = 1\%$).

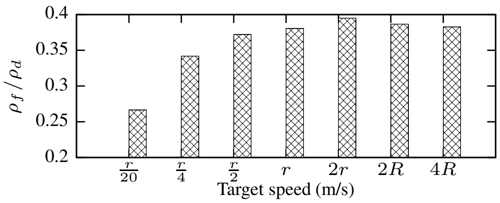


Figure 8. Density ratio *vs.* target speed (SNR $= 13\,\mathrm{dB}$, $\alpha = 5\%$, $\tau = 1.05$, $r = 2.25\,\mathrm{m}$, $R = 8\,\mathrm{m}$, $T = 1\,\mathrm{s}$).

α-delay under the disc model. Note that the lower bound given by Lemma 1 is also the analytical result of α-delay under the no-overlap case given in [8]. We can see that the simulation results confirm the analytical results under the disc model. Moreover, the α-delay significantly increases under the overlap case. Hence, the overlap/no-overlap condition has significant impact on the α-delay under the disc model.

We then evaluate the impact of false alarm rate and SNR on the density ratio. Figs. 6 and 7 plot the density ratio versus α-delay given various false alarm rates and SNRs, respectively. We can see from Fig. 6 that the disc model requires more than twice sensors when the α-delay approaches to one. Moreover, the density ratio decreases if a lower α is required, which is consistent with our analysis in Section V. From Fig. 7, we can see that the density ratio increases with SNR. For instance, if the SNR is $20\,\mathrm{dB}$, $\frac{\rho_f}{\rho_d}$ is greater than 1.2 and hence the disc model requires fewer sensors than the fusion model. Moreover, from the two figures, we can see that the density ratio under the overlap case is smaller than that under the no-overlap case. This is consistent with our observation that the overlap condition has little impact on the fusion model while leads to significant increase of α-delay under the disc model.

As target speed is an important factor of the overlap/no-overlap condition, we finally evaluate its impact on the density ratio. Fig. 8 shows the density ratio versus the target speed. We can see that the density ratio significantly increases when the target speed increases from $\frac{r}{20}$ to $2r$. This is due to the significant impact of overlap condition on the disc model, as observed in Fig. 5. Therefore, the data fusion model is more robust than the disc model in detecting slowly moving targets.

VII. Conclusion

In this paper, we study the impact of data fusion on QoSv of WSNs through the performance comparison between the disc model and data fusion model. The results show that data fusion is effective in achieving stringent QoSv requirements such as short detection delay and low false alarm rate, especially in the scenarios with low SNRs. In contrast, the disc model suffices only when the SNR is sufficiently high. The results help understand the applicability of the two models, and provide important guidelines for the design of surveillance WSNs.

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