TRAFFIC ESTIMATION FOR MAC PROTOCOLS IN DISTRIBUTED DETECTION WIRELESS SENSOR NETWORKS

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ABSTRACT

A major challenge in designing MAC protocols for wireless sensor networks (WSN) is the uncertainty about the traffic offered by network, which usually forces conservative assumptions leading to a degradation in throughput and delay performance. Traffic estimation is discussed here in the context of the distributed detection WSNs (DD-WSNs). We approach this issue by first showing that the traffic has a Poisson distribution via stochastic geometry tools. Then the traffic is estimated via two algorithms, the least conditional maximum a priori (lcMAP) estimator and the regularized maximum likelihood estimator (rMLE). To measure the correlation between supplied communication resources and needed resources by the WSN, we propose the supply demand ratio (SDR) as a metric. Simulation results shows that both estimators achieve a performance close to the optimal MAP estimator under low channel SNR, hence transmission energy can be saved. Furthermore, the rMLE achieves the optimal SDR via choosing regularization factor value.

Index Terms— Traffic estimation, distributed detection, stochastic geometry, wireless sensor networks.

I. INTRODUCTION

Distributed detection using WSN still is attracting attention in several application such as battle field surveillance [1], natural disasters alarming systems [2], or monitoring critical civilian structures [3]. This class of applications however, is primarily concerned with performing a specific task within a real-time deadline under many constraints of WSN operation [4]. Many factors are considered in the design of such systems, however, the MAC protocol design plays an integral role in such applications.

Many MAC protocols designed for WSNs have been proposed for general applications [5] and mission critical applications [6] as well. A major challenge in designing such MAC protocols is the uncertainty about the traffic offered by the WSNs that usually forces conservative assumptions leading to a degradation in throughput and delay performance.

In this paper however, we consider the problem of traffic estimation in the context of distributed detection WSN (DD-WSN). Given the special nature of traffic in distributed detection networks, we model the system using stochastic geometry to construct a statistical model of the traffic. Then statistical signal processing tools are used to estimate the traffic offered by the network. We show how this information can be incorporated in the structure of MAC protocols aimed at DD-WSN. Stochastic geometry has been used in modeling wireless networks [7], and coverage in WSNs [8]. In our previous work [9], we used stochastic geometry to characterize the detection performance of DD-WSN.

In this paper though, we extend the later work to show that the traffic in distributed detection WSN follows a Poisson distribution. Making use of this, traffic estimation is molded as a statistical parameter estimation problem. Using the powerful maximum a priori (MAP) estimator requires exact statistical information about the traffic, which is dependent on the true target hypothesis. Whereas using the simpler maximum likelihood estimator (MLE) degrades performance. Hence, we propose two algorithms to estimate traffic; the least conditional MAP (lcMAP) and the regularized MLE (rMLE). The lcMAP overcomes the lack of information about the target via using probability distribution under both hypotheses. On the other hand, the rMLE requires the knowledge of the mean traffic while providing comparable performance. Both algorithms provide good estimates under low SNRs, hence, transmission energy can be reduced, which consequently increases the network lifetime. Finally, we introduce the supply demand ratio (SDR) as a performance metric to gauge the match between the supplied communication resources and the network demand.

The paper is organized as follows; In Section II, the WSN is modeled using the stochastic geometry framework, and the assumptions on the communication channel are presented as well. Section III proposes the design of low-delay MAC protocols including traffic estimation with the lcMAP and rMLE in addition to the SDR metric. Simulation results and discussion is presented in section IV. Finally, we conclude the paper with Section V.

II. SYSTEM MODEL

Le the sensor nodes (SNs) in a WSN be modeled by a simple stationary isotropic homogenous Poisson point process (PPP) [10], say $\Phi = \{X_i\}$, where X_i is the location of the ith SN Φ has intensity of λ SN/m^2 in sensing field $\mathcal{A}$, where $\mathcal{A} \subset \mathbb{R}^2$. This model implicitly implies that X_i's are independent and identical distributed (iid) according to a uniform distribution $\mathcal{U}(\mathcal{A})$ and the number of the SN N is a Poisson random variable (RV) with mean λ. This assumption reflects the practical nature of WSNs in which SNs number changes randomly due to communication link outage and node failure. The SNs report back to a base station (BS) directly via a single hop shared MAC. The BS can be a cluster head amongst the SNs or a receiver mounted on board an unmanned aerial vehicle (UAV). We assume perfect synchronization and channel compensation between the FC and SNs.

The WSN is tasked with the distributed detection of any intrusion into the sensing field by periodically taking a snapshot of the field, every detection period, say$T$ second. Given the intruder, which we refer to as target, is mobile with relatively high speed, the snapshots of target's location are approximately independent [11]. Hence, studying a single snapshot is sufficient. At an arbitrary time snapshot nT, for $n \in \mathbb{N}$, the target takes a random location X_t such that $X_t \notin \Phi$. Let the target have a random amplitude A taken from known distribution $p(a)$, in every network realization. The emitted energy decays as it reaches the SN according to a power law with exponent $e \geq 1$, which reasonably describes acoustic or diffusive sources [12], [13] for $e = 1$.

Each SN collects $2K$ measurements that are corrupted by iid additive white Gaussian noise (AWGN) in space and time having zero mean and known variance σ_s^2. The measurements under the target's absence and presence hypotheses, $\mathcal{H}_0$ and $\mathcal{H}_1$ respectively, take one of the following forms

$$\mathcal{H}_0 : S_i[k] = W_i[k] \tag{1}$$

$$\mathcal{H}_1 : S_i[k] = \frac{A}{\|X_i - X_t\|^e} + W_i[k] \tag{2}$$

where $k = 0, \cdots, 2K-1$ and $W_i[k]$ is iid AWGN. Upon taking measurements at an arbitrary SN at X_i, the SN locally reaches a binary decision, $I(X_i) = \{0, 1\}$, about the presence of the target via a local detector. Since the target's parameters are unknown to the SNs, the energy detector is adopted as our local detector. The local probability of false alarm is [14]

$$P_{fa} = \Gamma(K, \frac{\gamma}{2})/\Gamma(\frac{\gamma}{2}) \tag{3}$$

where $\Gamma(\cdot,\cdot)$, $\Gamma(\cdot)$, and γ are the incomplete Gamma function, Gamma functions, and local detection threshold respectively. The later however, is assumed to be the same for all SNs for simplicity. On the other hand, the average local probability of detection for a given SN and target locations, x_i and x_t respectively, is [9]

$$P_d(x) = \mathbb{E}\left[Q_K\left(\sqrt{\frac{A^2}{\sigma_s^2 \|x_i - x_t\|^{2e}}}, \sqrt{\gamma}\right)\right] \tag{4}$$

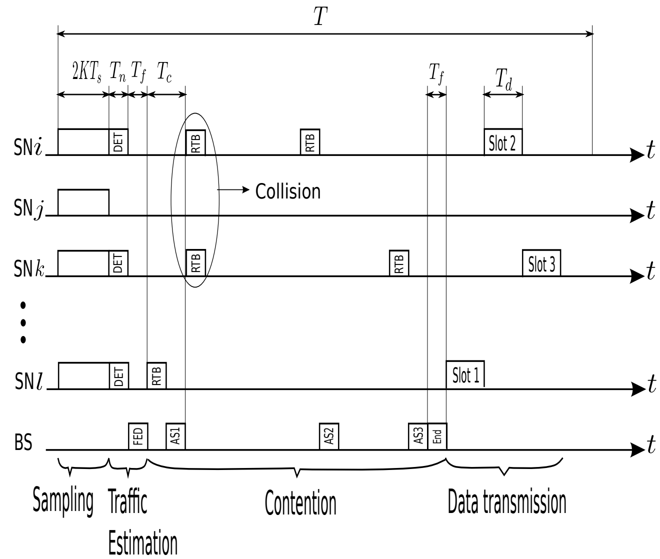


Fig. 1: MAC algorithm. The periods are T detection period, T_s sampling time, T_n notification time, T_f feedback time, T_c contention time, and T_d data transmission time. Packets are: DET detection notification, RTB request to book data slot, ASN assign data slot number N, and END contention stage end.

where is the expectation with respect to $p(a)$ and $Q_K(\cdot,\cdot)$ is the generalized Marqum Q-function.

In contrast to our previous work [9], in which detecting SNs send $I(X_i)$ to the BS, they transmit information about the target to the BS. This information might be a confidence measure of the local detection, a soft decision, or even estimates of the target [15]. This data is sent over a shared communication channel however, which is corrupted by AWGN with zero mean and known variance σ_c^2. The WSN employs a MAC protocol to regulate communication via firstly scheduling the SNs and then allocating a dedicated time slot for transmission. We assume that the contention and data transmission occurs in a time less than the detection period T.

III. TRAFFIC ESTIMATION FOR DD-WSNS

In this section, we describe the details of MAC protocol augmented with a traffic estimation phase. Then traffic estimation problem is presented for which the lcMAP and rMLE are put forward as a feasible alternatives for the MAP and MLE estimators. Finally, we propose a the SDR as a performance metric for distributed detection WSNs.

III-A. MAC Protocol Structure

The major issue in the MAC protocol design is identifying the nature of traffic, which arise due to having a random number of detecting SNs. Thus, having an estimate of the offered traffic enables the SNs to tune the MAC parameters, in fact the medium access probabilities P, to increase the successful transmission probability. Thus, we propose a

MAC protocol, similar to the contention based protocols in [6], that consist of three main stages: 1) Traffic estimation. 2) Scheduling (using contention). 3) Data transmission (using TDMA), as shown in Fig.1.

In the first stage, all the detecting SNs send the same notification packet DET to the BS in the notification slot T_n. The DET packet has N identical symbols each with E energy. Those packets add up coherently enabling the BS to estimate the received signal's amplitude, which is proportional to the number of detecting SNs or traffic. Then, the BS broadcasts the estimated traffic, $\widehat{\Theta} \approx \sum_{X_i \in \Phi} I(X_i)$, back to the SNs in T_f. In the second stage, the SNs set their access probability to $P = 1/\widehat{\Theta}$, which would be optimal in terms of transmission success probability. The SNs attempt to book a data time slot by sending the *request to book* RTB packet. If no collision occur with other RTB, the BS sends out a packet ASN assigning a specific data slot N to the requesting SN. The contention period continuous until the number of winners equals $\widehat{\Theta}$ or after a certain time is exceeded, after which the BS ends the contention phase by sending the END packet. In the last stage, the SNs transmit their data according to the assigned data time slots.

III-B. Traffic Estimation

In the traffic estimation phase, the BS receives the DET packets from all active SNs in the same time slot. The received signal at the BS adds up coherently to give

$$\begin{aligned} Y[n] &= \sqrt{E} \sum_{X_i \in \Phi} I(X_i) + V[n] \\ &= \sqrt{E}\Theta + V[n] \end{aligned} \tag{5}$$

where $V[n]$, $n = 0, \cdots, N-1$ are an iid AWGN with the distribution $\mathcal{N}(0, \sigma_c^2)$, and $\Theta = \sum_{X_i \in \Phi} I(X_i)$, which is the number of positive local detection decisions in the network. Hence, it is the number of SNs that will transmit data to the BS. The problem now is to estimate Θ from (5). A straightforward and simple estimator is the maximum likelihood estimator (MLE)

$$\widehat{\Theta}_{\text{MLE}} = \arg\min_{\Theta \in \mathbb{N}} \sum_{n=0}^{N-1} \left(y[n] - \sqrt{E}\Theta \right)^2 \tag{6}$$

where $y[n], \forall n$ is a realization of (5). The MLE finds the point in $\mathbb{N}$ closest to $y[n]/\sqrt{E}$. The MLE though, assumes that the traffic is an unknown constant, hence it does not use any prior information about the traffic. However, the traffic is actually a RV that depends on the detection probability of the SNs. The following propositions provide the statistical structure of the traffic under $\mathcal{H}_0$ and $\mathcal{H}_1$.

Proposition 1. *Given that the WSN is deployed as a stationary homogeneous PPP. Then, under hypothesis $\mathcal{H}_0$, the number of detecting SNs, and hence the traffic, is distributed according to a homogeneous Poisson RV with mean*

$$\mathbb{E}[\Theta] = \lambda P_{fa} \, |\mathcal{A}| \tag{7}$$

where $|\mathcal{A}|$ is the area of the sensing field.

Proof: Under hypothesis $\mathcal{H}_0$, the probability of detection is actually P_{fa}. In other words, the SN becomes active with a constant probability. Consequently, the traffic is the number of SNs in the independent (Bernoulli) thinned point process [10], with P_{fa} thinning probability. Hence, the number of such SNs is a Poisson RV with mean being $\lambda P_{fa} \, |\mathcal{A}|$. ■

Proposition 2. *For a stationary homogeneous PPP WSN using energy detector for local detector detection. The traffic under $\mathcal{H}_1$ is a inhomogeneous mixed Poisson RV with mean*

$$\mathbb{E}\left[\Theta\right] = \lambda \int_{\mathcal{A}} \mathbb{E}_A \left[Q_K \left(\sqrt{\frac{A^2}{\sigma^2 x^{2e}}}, \sqrt{\gamma} \right) \right] dx \tag{8}$$

Proof: Conditioned on A, the distribution of active SNs is a non-homogeneous Poisson RV [9], i.e. Poi $(\lambda P_d(x, A))$. Averaging over A yields the following mixed Poisson distribution

$$\Theta \sim \mathbb{E}_A \left[\text{Poi} \left(\lambda P_d(x, A) \right) \right] \tag{9}$$

and the mean follows as in (8). ■

The former proposition implies that the traffic under $\mathcal{H}_0$ is linearly proportion to the average number of SNs, $\lambda \, |\mathcal{A}|$, and the local probability of false alarm. On the other hand, the situation is more complex under $\mathcal{H}_1$, the traffic is dependent on the effective area denoted by the integral in the right hand side of 8. Given a traffic distribution, the MAP estimator can be used

$$\widehat{\Theta}_{\text{MAP}} = \arg\min_{\Theta \in \mathbb{N}} \sum_{n=0}^{N-1} \left(y[n] - \sqrt{E}\Theta \right)^2 - \log p(\Theta) \tag{10}$$

where $p(\Theta)$ is Θ's distribution. Although the MAP is the optimal estimator, it cannot be implemented since the distribution $p(\Theta)$ varies with $\mathcal{H}_i$ for $i = \{0, 1\}$. To overcome this obstacle though, we propose evaluating (10) for both hypotheses and choose the one with least value over all Θ points as our objective function, then choose the corresponding minimizer, since this cost function is expected to be one with the correct prior. We call this estimator *least conditional* MAP (lcMAP)

$$\begin{aligned} J_0(\Theta) &= \sum_{n=0}^{N-1} \left(y[n] - \sqrt{E}\Theta \right)^2 - \log p(\Theta|\mathcal{H}_0) && (11) \\ J_1(\Theta) &= \sum_{n=0}^{N-1} \left(y[n] - \sqrt{E}\Theta \right)^2 - \log p(\Theta|\mathcal{H}_1) && (12) \\ \widehat{\Theta}_{\text{lcMAP}} &= \arg\min\{\min_{\Theta \in \mathbb{N}} J_0(\Theta), \min_{\Theta \in \mathbb{N}} J_1(\Theta)\} && (13) \end{aligned}$$

The lcMAP estimator is expected to resemble the MAP estimator's performance, also it inherits the biased estimate of Θ as shown later in Section (IV). Reducing the bias is desirable, especially in our situation because of the dependance of communication time slot allocation on it. To this end, we reconsider (10) and (6) more carefully this time. We observe that (10) is a regularized form of (6), with the regularized term being the log-likelihood function. Replacing the later with a penalty acting on high deviations from the mean generally yields lower bias from the mean. Therefore, we suggest the following estimator that we name *regularized* MLE (rMLE)

$$J_2(\Theta) = \sum_{n=0}^{N-1} \left(y[n] - \sqrt{E}\Theta\right)^2 + \nu\left(\mathbb{E}\left[\Theta|\mathcal{H}_0\right] - \Theta\right)^2 \quad (14)$$

$$J_3(\Theta) = \sum_{n=0}^{N-1} \left(y[n] - \sqrt{E}\Theta\right)^2 + \nu\left(\mathbb{E}\left[\Theta|\mathcal{H}_1\right] - \Theta\right)^2 \quad (15)$$

$$\widehat{\Theta}_{\text{rMLE}} = \arg\min\{\min_{\Theta\in\mathbb{N}} J_2(\Theta), \min_{\Theta\in\mathbb{N}} J_3(\Theta)\} \quad (16)$$

where ν is arbitrary regularization factor chosen such that $\nu > 0$. The structure of the rMLE provides a controllable trade-off between the variance and the bias of the estimate through ν. This property proves very useful as shown in the simulation results.

III-C. Supply Demand Ratio

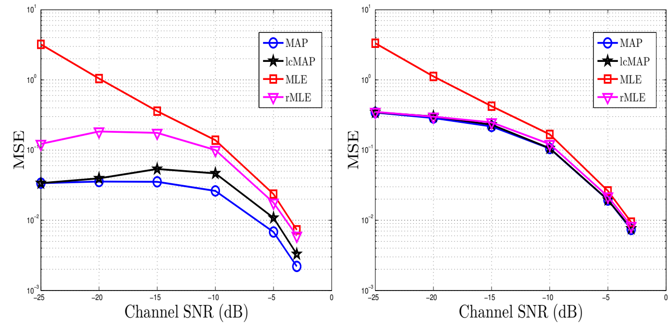
The suggested MAC estimates the traffic to provide the scheduler with the an estimate of the resource *demand* by WSN. In practice though, this estimate might vary from the actual demand, hence the *supply* of resources is different from the demand. Supplying less resources leads to loss of information whereas supplying more resources causes waste of them that in turn causes more delay and energy expenditure. We measure the performance of the MAC protocol, more specifically the traffic estimator impact on the MAC protocol by using the supply demand ratio (SDR) defined as

$$\text{SDR} = \frac{\mathbb{E}[\widehat{\Theta}]}{\mathbb{E}\left[\Theta\right]} \quad (17)$$

An optimal SDR takes a *unity* value. However, having SDR less than unity implies depriving SNs from communication resources, whereas a value greater than unity implies a waste of resources.

IV. RESULTS AND DISCUSSION

We simulate a WSN in a field of $300 \times 300\, m^2$ with SNs deployed according to a uniform random distribution therein. To exclude the edge effects we choose only SNs within $150\, m$ from the origin. The SNs are deployed with intensity $\lambda = 2 \times 10^{-3}\text{SN}/m^2$ with $P_{fa} = 10^{-3}$ each. Every SN takes 200 samples of a target having a Gaussian amplitude $A \sim \mathcal{N}(20, 8)$, located at the origin without loss of generality. The SNR is defined to be the target's emitted signal power over the noise power at the target's location, i.e., it is $\mathbb{E}[A^2]/\sigma^2$, which is chosen to be 10 dB. Each detecting SN send a 50 samples signal of constant level to the BS. This signal however, is corrupted by AWGN. We simulated the network for various channel SNRs. The simulation is run for 10^4 Monte Carlo iterations.



(a) $\mathcal{H}_0$ (b) $\mathcal{H}_1$

Fig. 2: The means square estimate (MSE) of MAP estimator, lcMAP, MLE, and the rMLE plotted against communication SNR

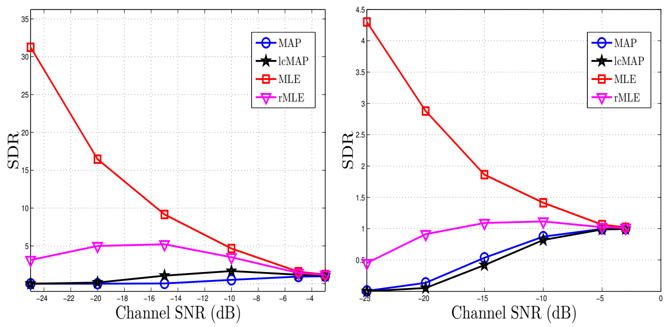
We compare the means sqaure error (MSE) of the estimators in Fig. 2 under both $\mathcal{H}_0$ and $\mathcal{H}_1$ hypotheses for low range of channel SNR. The rMLE design parameter is $\nu = 0.8$. Generally, all the estimators have relatively good performance and they significantly improve as the channel SNR increase. Under $\mathcal{H}_0$, the lcMAP estimator outperforms both MLE and rMLE estimators, in fact it approaches the optimal MAP MSE. However, under $\mathcal{H}_1$ both the lcMAP and rMLE significantly approach the MAP. The behavior of the lcMAP is simply explained by (13), in which it chooses the cost function closer to the true MAP. As for the rMLE, the good performance is due to the regularization that has more effect compared with the $\mathcal{H}_0$ case.

The SDR metric is shown in Fig. 4. The MLE shows the worst performance by supplying more than needed resources, especially under $\mathcal{H}_0$ due to the small average traffic. This trend also continues under $\mathcal{H}_1$ although less severely. The lcMAP and MAP exhibit similar performance, in contrast to the MLE though, deprive the SNs from resources. Whereas the rMLE shows the best SDR approaching unity for most SNR values under both hypotheses. This is again attributed to the penalization of large deviations form the mean and to the suitable regularization factor ν.

This affect of the regularization factor on the SDR is depicted in Fig. 4 for a channel SNR of -25 dB under $\mathcal{H}_1$. As evident from the figure, various SDR values can be attained by varying ν. The optimal value however, matching the supply and the demand in the WSN, is around 1.4.

V. CONCLUSION

We present a traffic estimation algorithms for distributed detection in WSNs. Using tools from stochastic geometry,



(a) $\mathcal{H}_0$ (b) $\mathcal{H}_1$

Fig. 3: The mean estimate of MAP estimator, lcMAP, MLE, and the rMLE plotted against communication SNR.

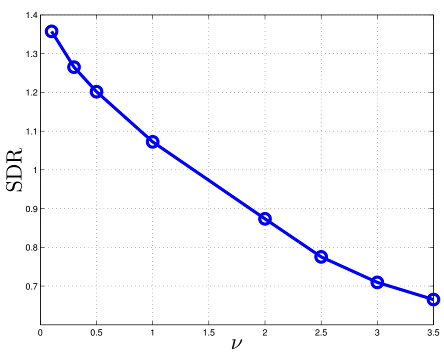


Fig. 4: The supply demand ratio (SDR) of the rMLE plotted against the regularization factor ν under the target present hypotheses, $\mathcal{H}_1$ and channel SNR of -25 dB.

the traffic is shown generally to be a Poisson random variable. This results facilitates casting the problem as a parameter estimation and solved using statistical signal processing methods.We propose two algorithms to estimate the traffic in addition to the conventional MLE and MAP algorithms. The least conditional MAP (lcMAP) is proposed with performance closely approaching the optimal MAP algorithm, however still requiring full statistical knowledge of the traffic. As a result, the regularized MLE (rMLE) is proposed that only requires the mean of the traffic. Both the lcMAP and rMLE provide good estimates under relatively low SNRs. Thus, reducing the needed transmission energy of the SNs, which consequently prolongs the network lifetime. Furthermore, the proposed algorithms provide a trade-off between delay and throughput. The SDR is proposed as a measure of the traffic estimation impact. Optimal SDR values of unity is attained only by the rMLE through choosing an appropriate value for the free design parameter.

For future work, we intend to investigate the case of fading channels between the SNs and the BS. In addition to theoretical characterization of the delay and throughput in DD-WSN.

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