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Distributed inference in wireless sensor networks

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Statistical inference is a mature research area, but distributed inference problems that arise in the context of modern wireless sensor networks (WSNs) have new and unique features that have revitalized research in this area in recent years. The goal of this paper is to introduce the readers to these novel features and to summarize recent research developments in this area. In particular, results on distributed detection, parameter estimation and tracking in WSNs will be discussed, with a special emphasis on solutions to these inference problems that take into account the communication network connecting the sensors and the resource constraints at the sensors.

Keywords: distributed detection; distributed estimation; target tracking; decentralized detection and estimation

1. Introduction

With significant advances in the areas of computer/communication networking, wireless communications, micro-fabrication and integrated circuits technology, the field of wireless sensor networks (WSNs) has grown rapidly and received considerable attention in recent years [1,2]. Sensor nodes in WSNs are typically small battery-powered devices that have limited sensing, computation and communication capabilities. Nevertheless, owing to their high flexibility, enhanced surveillance coverage, robustness, mobility and cost-effectiveness, WSNs have great potential in many applications such as environmental monitoring, battlefield surveillance or structural health management.

Applications of WSNs invariably involve some kind of statistical inference about the environment, i.e. detection, parameter estimation or tracking. Detection often serves as the initial goal of a sensing system. For example, in the context of environmental monitoring, it is of interest to first detect the presence of a contaminant, before determining the level of contamination. For systems observing infrequent events such as surveillance systems, detection may be the prevalent function of the network. Parameter estimation is another canonical problem in sensor networks. As an example, consider the problem of estimating the location and intensity of a heat source based on measurements taken by a

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set of thermal sensors that are remote to the source. Tracking can be considered to be a dynamic version of the estimation problem where the state of nature is time-varying. In tracking problems of practical interest, the physical locations of one or more moving objects need to be tracked by observations taken at the sensors. For example, the sensors could be used for work in process tracking in a manufacturing environment.

Since the information available for detection, estimation and tracking in WSNs is distributed across the sensors in the network, these decision-making problems fall under the umbrella of distributed inference. The goal of this paper is to provide the reader with an overview of the state of the art in distributed inference in sensor networks.

2. Detection and parameter estimation

Distributed detection with fusion was an active research field during the 1980s and early 1990s, starting with the seminal work described by Tenney & Sandell [3]. The application driver for this research was distributed radar with a central command (fusion) centre. The goal was to design the radars and the fusion centre to detect an event as accurately as possible, subject to an alphabet-size constraint on the messages transmitted by each sensor node. A survey of early work in this field is provided by Tsitsiklis [4], Viswanathan & Varshney [5], Blum *et al.* [6] and Varshney [7]. There has been renewed interest in distributed detection in the context of modern WSNs (see [8,9] for recent surveys). There are two main features of the emerging approach to distributed detection (and more general distributed inference problems). The first is the inclusion of more general communication architectures for the network, in particular sensor-to-sensor wireless communication. The second is the inclusion of strategies for sensor resource management, in particular energy consumption.

Distributed detection and parameter estimation problems will be discussed in this section, followed by a discussion of tracking in §3.

(*a*) *Wireless sensor network topologies*

The design of distributed detection and estimation algorithms depends on the underlying sensor network topology. The star topology [7], as shown in figure 1*a*, is the most common structure and has been studied quite extensively. In this configuration, the different sensors make observations of the underlying phenomenon and transmit functions of the observations, which could be local decisions, directly to the fusion centre via wireless channels. Another popular structure is the serial, or tandem, topology [10]. In the serial topology, all the sensors are connected in series and receive direct observations of the phenomenon. The decision of the first sensor is based only on its observation, and this decision is transmitted to the second sensor, which uses the decision of the first sensor in conjunction with its direct observation. The decision of the last sensor is accepted as the final decision of the network. In addition to these extreme configurations, one can envision configurations that are combinations of these basic topologies, e.g. tree or hierarchical topologies [11,12], or even completely distributed topologies where the sensors communicate with each other over a wireless ad hoc network [13–15], as shown in figure 1*b*.

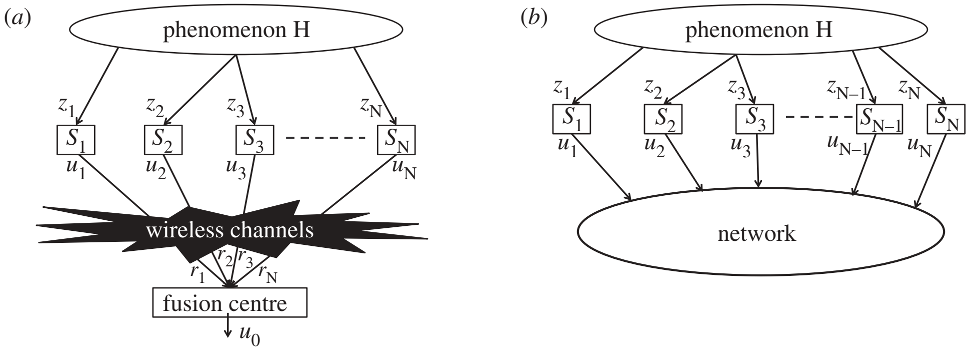

Figure 1. (*a*) Star topology and (*b*) distributed topology.

(*b*) *Distributed detection basics*

For the star topology, two inherently different problems need to be considered for the distributed detection problem: the design of the decision rule at the fusion centre (often referred to as the fusion rule), and the design of the local sensor decision rules. In order to optimize the detection performance, the decision rules at the local sensors and at the fusion centre are designed under criteria such as the Bayesian or Neyman–Pearson criterion (e.g. [7,16]). The decision rules at the fusion centre and at local sensors are intertwined with each other and need to be jointly determined to optimize the overall system performance. The design of fusion rules is conceptually straightforward assuming a perfect knowledge of system parameters. The optimum fusion rule amounts to a likelihood ratio test (LRT) and has been characterized for both binary and multibit (soft) local sensor outputs [7].

Obtaining local sensor decision rules is considerably more complicated. The optimality of LRTs at the local sensors has been established under the *conditional independence assumption* [4,5] that the sensor observations are independent, given the underlying hypothesis. However, establishing the optimality of LRTs at local sensors does not completely solve the problem, since the LRT thresholds at the sensors and the fusion rule are coupled with each other and they affect the system performance in an interdependent manner. Therefore, the local sensor thresholds are usually obtained through a person-by-person optimization (PBPO) approach, where each threshold of the sensor is optimized assuming fixed decision rules at all other sensors and the fusion centre. This approach is only guaranteed to produce a locally optimal solution and not necessarily a globally optimal solution.

Even PBPO solutions become intractable when the size of the sensor network becomes large, and simpler solutions are needed. It was shown by Tsitsiklis [17] that, for the binary hypothesis testing problem, using identical local decision rules for all the sensor nodes is asymptotically optimal in terms of the error exponent. Chamberland & Veeravalli [18] showed that, by considering the asymptotic regime, binary sensors are optimal if there exists a binary quantization function whose Chernoff information exceeds half of the information contained in an unquantized observation. This requirement is fulfilled by many practical applications [19] such as the problem of detecting deterministic signals in a

Gaussian noise and the problem of detecting fluctuating signals in a Gaussian noise using a square-law detector. In these scenarios, the gain offered by having more sensor nodes outperforms the benefits of getting detailed information from each sensor.

(*c*) *Robust and composite distributed detection*

The design of optimal decision rules for decentralized detection problems is based on the assumption that the probability distributions of the sensor observations (under each hypothesis) are known. In many applications, however, the distributions of the sensor observations are only specified as belonging to classes which are referred to as *uncertainty classes*. The problem here is to design decision rules that are robust with respect to uncertainties in the distributions. A common approach for such a design is the minimax approach where the goal is to minimize the worst-case performance over the uncertainty classes. Extensions of the minimax robust detection problem to the decentralized setting are discussed by Geraniotis & Chau [20] and Veeravalli *et al.* [21].

Another approach that does not require the knowledge of individual sensor statistics is to use the total number of '1's as a statistic since the information about which sensor reports a '1' is of little use to the fusion centre. For a WSN with randomly deployed sensors, Niu & Varshney [22,23] investigate the performance of such a *counting rule*, where the fusion centre employs the total number of detections reported by local sensors for hypothesis testing.

When the signal intensity is assumed to be inversely proportional to a power of the distance from the source, the sensor decisions become conditionally independent as long as the source location is known exactly. Niu & Varshney [24] proposed a generalized likelihood ratio test (GLRT)-based decision fusion method that uses quantized data from local sensors to jointly detect and localize a target in a wireless sensor field. The GLRT-based fusion rule significantly improves detection performance compared with the counting rule. Moreover, in a scenario where the sensors that are located within the radius of influence of the source receive identical signals and the rest of the sensors do not sense the source, the false discovery rate can be used to determine good local sensor decision rules [25].

(*d*) *Channel aware distributed detection*

The distributed detection problem in the presence of non-ideal communication channels has also been studied quite extensively in recent literature. Under the Bayesian criterion, the optimality of the LRT for local sensor decisions has been established for a binary hypothesis testing problem in a sensor network with non-ideal channels [26]. For a finite number of sensors, Cheng *et al.* [27] provide the conditions under which the channel outputs no longer reduce the error probability at the fusion centre. Channel aware decision fusion algorithms have been investigated with different degrees of channel state information for single-hop [28–30], multi-hop [31] and serial topologies [32] for distributed detection in WSNs. Furthermore, channel-optimized local quantizer design methods are provided by Liu & Chen [33]. To counter sensor or channel failures, robust binary quantizer design has been proposed by Lin *et al.* [34]. Channel aware distributed detection has also been studied in the context of cooperative relay networks [35].

(*e*) *Correlated observations*

While the popular assumption that observations at the sensors are conditionally independent is convenient for analysis, it does not necessarily hold for arbitrary sensing systems. For instance, if the signal is random and sensor nodes lie in close proximity of one another, their observations remain strongly correlated, even after conditioning on the hypothesis. Distributed detection problems with correlated observations can be considerably more challenging than their conditionally independent counterparts [36]. A variety of approaches have been proposed to address these challenges. Willett *et al.* [36] give a thorough analysis of the binary quantization of a pair of dependent Gaussian random variables. The findings in this paper indicate that, even in this simple setting, an optimal detector may exhibit very complicated behaviour. In Kam *et al.* [37], the structure of an optimal fusion rule has been examined for the more encompassing scenario where multiple binary sensors observe conditionally dependent random variables. In Blum & Kassam [38], the structure of an optimal detector when faced with weak signals and dependent observations has been explored. Chen & Ansari [39] have proposed an adaptive fusion algorithm for an environment where the observations and local decisions are dependent from one sensor to another. This adaptive approach requires the knowledge of only a few system parameters. Additional studies have explored the effects of correlation on the performance of distributed detection systems [40,41] and Blum [42] has provided a discussion of locally optimum detectors for correlated observations based on ranks.

The theory of large deviations can be used to assess the performance of wireless sensor systems exposed to correlated observations [43,44]. In particular, the Gärtner–Ellis theorem and similar results from large-deviation theory have been successfully employed to assess the asymptotic performance of large, one-dimensional systems [45]. For differentiating between known signals in a Gaussian noise, overall performance improves with sensor density, whereas, for the detection of a Gaussian signal embedded in Gaussian noise, a finite sensor density is optimal [44]. Results of large deviations have also been applied to the problem of hypothesis testing against independence for a Gauss–Markov random field, where the error exponent for the Neyman–Pearson hypothesis testing is analysed for different values of the variance ratio and correlation [46].

Sundaresan *et al.* [47] and Iyengar *et al.* [48] employed copula theory for signal detection problems involving correlated observations as well as for heterogeneous sensors, observing a common scene. For the fusion of correlated decisions, copula theory does not require prior information about the joint statistics of the sensor observations or decisions, and allows the construction of the joint statistics based on a copula selection procedure.

(*f*) *Sequential and quickest change detection*

In the dynamic setting, each sensor receives a sequence of successive observations and the detection system has the option to stop at any time and make a final decision, or to continue taking observations. The simplest problem in this setting is that of binary *sequential* detection. A distributed version of binary sequential detection, where sensors make final decisions (linked through a common cost function) at different stopping times, has been studied by Teneketzis & Ho [49] and Veeravalli *et al.* [50]. Fusion of sequential decisions made at the sensors has been considered in Hussain [51]. A more general formulation of the fusion problem was introduced by Hashemi & Rhodes [52], and a more complete solution to this problem was given by Veeravalli and co-workers [21,53]. Recent work includes an asymptotic theory for sequential hypothesis testing in sensor networks in the regime of small-error probabilities [54].

A different binary sequential decision-making problem that first arose in quality control applications is the *quickest change detection* problem [55]. Here, the distribution of the observations changes abruptly at some unknown time, and the goal is to detect the change as soon as possible after its occurrence, subject to constraints on the false alarm probability. A decentralized formulation of the quickest change detection problem has been considered by Crow & Schwartz [56] and Teneketzis & Varaiya [57], with the sensors implementing individual change detection procedures. Practical schemes for fault detection with multiple observers have been proposed by Wang & Schwartz [58]. A general formulation of decentralized quickest change detection with a fusion centre making the final decision about the change was introduced by Veeravalli [53,59], and multi-channel extensions discussed by Tartakovsky & Veeravalli [60]. The extension to the situation where the change takes place at different times at the sensor, i.e. the change is a *process* across the sensors, is considered by Raghavan & Veeravalli [61].

(*g*) *Detection based on multi-objective optimization*

Sensor network design involves simultaneous consideration of multiple conflicting objectives, such as maximizing the lifetime of the network or maximizing the detection capability, while minimizing the transmission costs. For example, it may be best for a node to avoid sending data when the information content of a transmission is small [62–65]. An added benefit of the censoring approach is that, under a send/no-send constraint on each sensor and when the fusion centre has its own observations, the sensor decision rules can be determined independently without any loss of optimality [63].

Multi-objective optimization methods [66–72] consider possibly conflicting objectives simultaneously and generate a set of solutions reflecting different trade-offs between the objectives. Then sensor decision thresholds not only determine the probability of error in the network, but also determine the total energy consumption of the network. Rather than minimizing the probability of error of the WSN subject to a resource constraint, in the approach presented by Masazade *et al.* [73], the problem of obtaining the sensor decision thresholds is formulated as a multi-objective optimization problem (MOP). Instead of having a single solution that minimizes the probability of error of the network in a Bayesian framework, by using the MOP approach, several sensor threshold solutions are determined which deliver significant energy saving compared with the energy consumption of the minimum probability of error solution without sacrificing much from the best achievable probability of error.

(*h*) *Distributed parameter estimation*

While much of the initial work on distributed inference in sensor networks was restricted to detection problems, more recently there has been considerable interest in distributed parameter estimation. There have been a number of papers on distributed parameter estimation under the star topology depicted in figure 1*a*, e.g. [74–76]. For one-bit quantization at the sensors, it has been shown that the maximum likelihood estimate achieves the Cramér–Rao lower bound (CRLB) asymptotically when the number of sensors is large [76]. When the observation noise is small, adding a Gaussian dithering noise or some deterministic signals at the local sensors may lower the CRLB [77]. It has also been shown that using one-bit uniformly dithered samples instead of the unquantized, full-precision data only suffers a logarithm rate loss, for single- and multiple-parameter estimation [78,79].

For the case where the joint distribution of the sensor observations and the parameter is not completely available, several distribution-independent distributed estimation schemes have been proposed under the assumption that the sensor noises are bounded, zero mean and identically independent distributed (i.i.d.) [80–82]. Although the resulting estimators have been shown to be unbiased or asymptotically unbiased, the estimation variance is largely unknown but bounded. Chen & Varshney [83] have considered the non-parametric distributed parameter estimation problem using one-bit quantized data from peripheral sensors. Assuming that the sensor observations are bounded, non-parametric distributed estimators are obtained based on the knowledge of certain moments of the sensor noises. These estimators are shown to be either unbiased or asymptotically unbiased with bounded and known estimation variance. The proposed estimators are shown to be consistent even when local sensor noises are not independent but m-dependent. Performance in terms of the minimax CRLB metric has been considered and discussed by Venkitasubramaniam *et al.* [84] and Chen & Varshney [85].

Distributed parameter estimation problems for more general sensor network topologies (as described in figure 1*b*) have also been studied. For example, the ring-network structure has been considered [86–88] for in-network information processing, where the sensors are organized in a cycle and process the information by passing the estimates along the cycle. Consensus-based approaches for distributed estimation have been discussed [14,89–92]. In addition, specific approaches to distributed estimation of diffusive sources have been studied [15,93,94].

3. Tracking

The design of object (target) tracking algorithms using a small number of sophisticated sensors (e.g. radars) is a well-studied problem (e.g. [95–98]). Many of the basic problems, such as trajectory modelling, nonlinear filtering and data association, carry over to the problem of tracking in WSNs with a large number of sensors. The use of sensor networks for tracking, however, presents a number of new challenges. These challenges include distributed algorithms and control, energy efficiency and understanding the fundamental performance limits of sensor networks for tracking applications, especially as the size of the network becomes large. We will pay special attention to these new challenges in this section.

(*a*) *Nonlinear filtering and particle filtering*

A standard and reasonable assumption that is made in most tracking problems is that the state (location of the object) evolves as a Markov process, with the

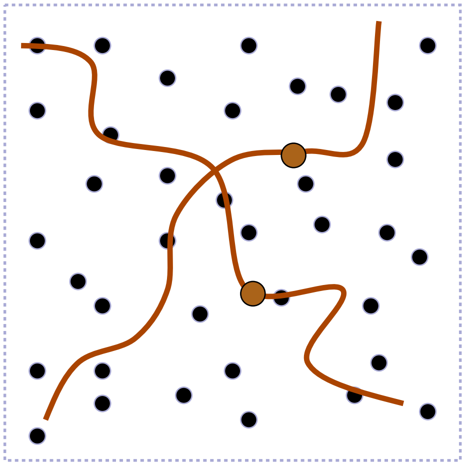

Figure 2. Tracking objects using a sensor network. (Online version in colour.)

observations being functions of the state corrupted by noise (figure 2). In the Bayesian sequential framework the statistical model for the system evolution with time is assumed to be known *a priori*. A basic step in tracking the object is the recursive evaluation of the *a posteriori* probability distribution of the state given the past observations, also know as the *belief state*. The recursive update of the belief state can be broken into two stages: *prediction* based on the Markov prior, and *update* using the new observations and Bayes rule.

In the simplest case, we have a linear state space model with Gaussian innovations and observation noise, for which the linear Kalman filter provides the update for the belief state [16]. Variations of the Kalman filter, such as the extended Kalman filter and unscented Kalman filter, can be used to provide the belief update in some cases where the linear, Gaussian model is relaxed [99].

More generally, the belief state update involves a complicated nonlinear filtering operation, which can be computationally intractable. Tractable solutions can be obtained via the non-parametric Monte Carlo sampling-based method of *particle filtering* [98,100]. The idea behind particle filtering is to represent (approximate) the belief state in terms of a discrete distribution on the set of samples of the state. The sample points and weights (point masses) associated with the samples are updated using the Markov state evolution and observation models. There are a variety of ways of performing the particle update; see Arulampalam *et al.* [100] and Doucet & Johansen [101] for recent summaries.

In a sensor network, there are two options for performing the belief update: it can be done centrally at a fusion centre or in a *distributed* manner across the sensors. Centralized processing, while being straightforward, may require a considerable overhead for communication between the sensors and the fusion centre. In the distributed case, the sensors maintain belief states on their own and exchange messages among themselves to update their beliefs. A distributed version of the Kalman filter is described by Olfati-Saber [102], and distributed versions of particle filters have been studied by Coates [103] and Gu and co-workers [104,105]. Distributed tracking using particle filters that explicitly take into account the channel connecting the sensors and the fusion centre is described by Ozdemir *et al.* [106].

(*b*) *Multi-object tracking and data association*

Tracking multiple objects is not a simple extension of tracking a single object owing to the *data association* problem. This problem arises whenever the identity of the objects cannot be determined from the observations. Thus, even if all object locations are known exactly, it may not be known which location corresponds to which object. This uncertainty leads to an explosion in the set of possibilities that must be considered in determining the belief states for the objects (tracks) given the observations [107–109].

There are two main approaches to dealing with the data association problem, while maintaining a reasonable level of computational complexity. The first is an approach proposed by Fortmann *et al.* [110] called *joint probabilistic data association* (JPDA) in which the belief state of each track is updated using a weighted combination of all the observations. The weights are chosen based on estimates of the probabilities that a given observation is associated with a given track, while ensuring that mutual exclusion of the tracks is maintained at all times.

The second approach to dealing with the data association problem called *multiple hypothesis tracking* (MHT) was proposed by Reid [111]. The idea is to keep multiple possible associations (or hypotheses) of observations to existing tracks, new tracks and possible false alarms. The actual data association decisions are hence effectively delayed until enough data are available to resolve the true hypothesis with high confidence. An advantage of the MHT approach over the JPDA approach is that the number of tracks need not be known beforehand. However, an obvious disadvantage of the MHT approach is that the storage and processing requirement might be considerably higher than that for the JPDA approach.

There are a number of variants of the JPDA and MHT approaches described in the survey paper by Liu *et al.* [107], where considerations such as resource constraints at the sensors are also discussed. Specific approaches to multi-object tracking using distributed nonlinear filtering and data association techniques are also described by Oh *et al.* [112].

(*c*) *Sensor management, scheduling and sleep control*

An important aspect of tracking using sensor networks is the efficient management of the sensor resources, where at each time step the modes of the sensor are controlled based on the information available up to that time. Typically, the sensor control simply decides which sensors should be on at a given time instant, with the goal of optimizing the trade-off between energy consumption and tracking performance. The control problem can be cast within the framework of partially observable Markov decision processes (POMDPs), and it is easily shown that the belief states of the objects serve as sufficient statistics for the control, as shown in figure 3.

Such a control problem was studied by Castanon [113] in the context of classification of a large number of unknown objects, where an approximate dynamic programming approach for dynamic scheduling of multi-mode sensor resources was developed. The goal [113] was to achieve an accurate classification of each object at the end of a fixed finite horizon by assigning different sensor modes to different objects subject to periodic or total resource usage constraints.

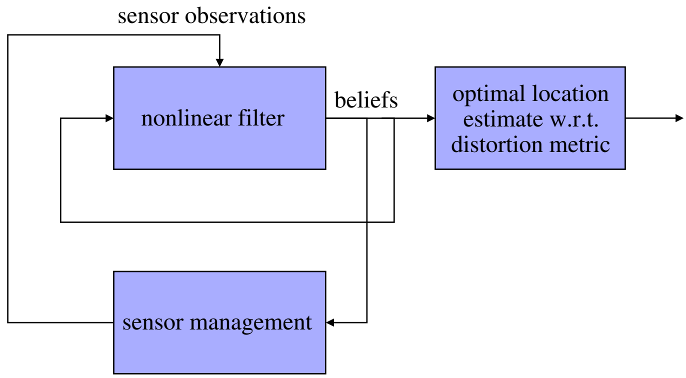

Figure 3. Sensor management for tracking. (Online version in colour.)

Mode allocation strategies are computed based on Lagrangian relaxation for an approximate optimization problem wherein sample-path resource constraints are replaced by expected value constraints. In the context of sensor scheduling for target tracking, information-based approaches [114,115] have been developed for optimizing tracking performance subject to an explicit constraint on communication costs in a decentralized setting. The Lagrangian relaxation approach is also adopted [114] to solve a constrained dynamic programme over a rolling horizon. There, the combinatorial complexity of the decision space is avoided by first selecting one leader node, followed by greedy sensor subset selection. Other related work on sensor scheduling includes leader-based distributed tracking schemes [116,117], where at any time instant one sensor, the leader sensor, is active, and the leader changes dynamically as a function of the object state, while the rest of the network is idle. Comparisons between scheduling and random sensor activation are made by Pattem *et al.* [118], who show that orders of magnitude savings in energy are possible with scheduling. There has also been some recent work on coordinated guidance of autonomous unmanned aerial vehicles for multi-target tracking using POMDPs [119].

More recently, a fundamental study [120] of the problem of optimizing the trade-off between energy consumption and tracking performance has been undertaken. A variety of sensing and object movement models were studied [120], and in many cases computable lower bounds on the optimal trade-off are given that can be used as benchmarks in comparing implementable suboptimal procedures. The suboptimal procedures proposed [120] are shown to approach the lower bound in the low tracking error regime of interest in applications.

(i) *Reduced complexity metrics for tracking*

The complexity of the dynamic programming optimization, even for myopic policies, can be difficult owing to intractability of the metrics used in the optimization. Therefore, approaches based on reduced complexity metrics have been adopted, and these approaches largely fall into two categories. The first is based on information-theoretic measures, such as entropy, relative entropy and Rényi divergence, and the second is based on the posterior CRLB (PCRLB). In the context of Bayesian estimation, a good measure of the quality of a sensing action is the reduction in entropy of the posterior distribution that is expected to be induced by the measurement. Therefore, it may be beneficial to choose the sensing action that maximizes the expected gain in information based on a variety of information-theoretic measures [114,115,121–125].

A possible shortcoming of the information-theoretic approaches is that computational complexity may still be large, especially when the number N of sensors to be selected is large. In particular, it has been shown [126] that the complexity of mutual information-based approaches is exponential in N, whereas the complexity of PCRLB or conditional PCRLB-based approaches is linear in N. A recursive approach to calculate the sequential PCRLB for a general multi-dimensional discrete-time nonlinear filtering problem has been derived [127]. Many researchers have proposed PCRLB-based approaches to solve sensor management problems [128–131]. In these approaches the unconditional PCRLB is employed, where the Fisher information matrix is derived by taking the expectation with respect to the joint distribution of the measurements and the target states up to the current time, making it an off-line bound. The unconditional PCRLB is determined by using only the system dynamic model, system measurement model and the prior knowledge regarding the target state at the initial time, and is thus independent of any specific realization of the target track. As a result, the unconditional PCRLB does not reflect the target tracking performance for a particular track realization faithfully. Some ad hoc attempts have been made to fix the above problem but these solutions are not theoretically justified. To take advantage of the available measurement information, an exact conditional PCRLB that is dependent on the past data and hence is implicitly dependent on the target track up to the current time has been derived [132]. A recursive approach to calculate the conditional PCRLB for nonlinear/non-Gaussian Bayesian estimation problems, and also a numerical approximation for its computation through particle filters, has been presented [132]. This conditional PCRLB is computationally efficient and suitable for sensor management.

(ii) *Sensor sleep control for tracking*

An inherent assumption in the sensor scheduling work described above is that the sensors can be switched between the on and off states by external means. Either the method used for this wake-up is left unspecified or it is assumed that there is some low-power wake-up radio at each sensor dedicated to this function. A more practical assumption in many sensor networks is that a sensor that is asleep cannot be communicated with or woken up, and hence the sleep duration needs to be determined at the time the sensor goes to sleep. A straightforward approach is to have each sensor enter and exit the sleep mode using a fixed or a random duty cycle. A more intelligent, albeit more complicated, approach is to use information about the objects' trajectories that is available to the sensor from the network to determine the sleeping strategy. Such an approach was introduced by Fuemmeler & Veeravalli [133], who studied a single object tracking problem under a simple sensing and object movement model. A computable lower bound on the optimal trade-off between energy consumption and tracking performance is presented, and strategies that come close to this bound are presented. Furthermore, it is shown by Fuemmeler & Veeravalli [133] that the nearly optimal strategies result in considerable savings in energy over duty cycle policies. Generalizations to multi-object tracking are presented by Fuemmeler & Veeravalli [134], and sleeping policies for under general models for object movement, object sensing and tracking cost are presented by Fuemmeler *et al.* [135].

4. Conclusions

In conclusion, distributed inference in WSNs is a rich and vibrant area of research. There has been much progress in this area over the last couple of decades, particularly in terms of understanding how to effectively deal with resource constraints such as energy and communication bandwidth and range. However, a number of interesting questions remain. Our understanding of distributed inference problems when the observation statistics are unknown is still far from complete; new learning-based approaches that work when the statistics are unknown or partially known need to be developed. Progress on distributed inference with conditionally dependent observations has been limited and new techniques for both the design and analysis of effective algorithms are required. Also, a topic that has not received much attention is the design of communication architectures that are best suited for the inference problem being addressed. Another challenging open problem in distributed inference is when *heterogeneous* sensors, e. g. of different modalities, are observing the same phenomenon. Finally, when humans are part of the inference process along with physical sensors, many new problems arise owing to the nature of their information (soft versus hard information) and human limitations on information acquisition and processing such as their categorization of priors [136]. Such distributed inference problems become important with the ever-increasing role that social networking is playing in our lives.

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