ISBN : 978-1-60558-710-3

The ACM International Conference Proceeding

ICIS 2009

The 2nd International Conference on Interaction Sciences: Information Technology, Culture and Human.

24-26 November, 2009
Seoul, Korea

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Averaging Approach for Distributed Event Detection in Wireless Sensor Networks

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ABSTRACT

We consider the problem of classifying among a set of M hypotheses via distributed noisy sensors. The sensors can collaborate over a communication network and the task is to arrive at a consensus about the event after exchanging messages. We reformulate the problem and apply distributed averaging algorithm as a strategy for collaboration to arrive at a solution, which is equivalent to the centralized *maximum a posteriori* (MAP) estimate. Some distributed averaging algorithms and strategies for choosing them are also introduced.

Keywords

Event detection, distributed averaging, collaborative framework.

1. INTRODUCTION

Recently, wireless sensor networks (WSNs) have attracted much attention and interest, and have become a very active research area. Due to their high flexibility, enhanced surveillance coverage, robustness, mobility, and cost effectiveness, WSNs have wide applications and high potential in military surveillance, security, monitoring of traffic, and environment. Usually, a WSN consists of a large number of low-cost and low-power sensors, which are deployed in the environment to collect observations and preprocess them. Each sensor node has limited communication capability that allows it to communicate with other sensor nodes via a wireless channel. In typical applications, energy limitation of individual sensors is a primary bottleneck as it entails further constraints in communication bandwidth, reliability and connectivity. Information processing models that account for such limitations have recently received much attention within the networking, signal processing and information-theory communities.

ICIS 2009, November 24-26, 2009 Seoul, Korea

We consider a collection of sensor observing a single phenomenon through noisy measurements. The sensors can only collaborate through a network defined by a connectivity graph. The task is to exchange messages in order to arrive at a consensus that reflects the classification of the event by a hypothetical node that have access to all observations and observation models.

The general question of dealing with distributed data in the context of detection has been an active topic of research (see [1], [2], [11]–[17] and references therein). Previously proposed techniques can be broadly categorized into two groups: The fusion-centric approach assumes that each sensor has a communication link to a data fusion center. Quantization of sensor data in this model was addressed by [16], [17], effects of power constraints on noisy communication channels were considered in [11], [12]. The ad hoc approach, on the other hand, involves no designated fusion center but focuses on establishing consensus within the network via message exchanges. This approach is arguably more suitable to address energy issues in large scale networks and also appears to have robustness advantages.

Early literature [3] establishes that consensus is achieved if messages are conditional expectations adapted to local measurements and messages, however the agreement itself is in general sensitive to the relative timing of messages, and computing the conditional expectations is not practically appealing. Message specification and rigid messaging schedules that lead to consensus on optimal decisions were given in [18] for the special case of a completely connected communication topology.

Some variants of belief propagations [1], [19] have been used as a message passing strategy to solve the distributed event detection problem for a pre-specified and unchanged network topology. However, these algorithms may fail to converge or converge to an inaccurate estimate due to the unknown of asymptotic features in general network topology. Furthermore, the assumption of unchanged network topology is obviously inapplicable to WSNs where sensors are usually randomly deployed and network topology may change because of obstacles, node failures, etc.

In this paper, we reformulate the distributed event detection problem into a distributed averaging problem, and then propose using existing distributed averaging algorithms to solve the problem. The paper is organized as follows. In section II we formally define the problem. Section III presents our approach using distributed averaging algorithms. In section IV we evaluate the performance of this approach. Finally, conclusions are given in section V.

2. PROBLEM FORMULATION

The WSN is represented by a directed graph $G=(V,E)$, which is assumed to be strongly connected in order to avoid trivialities. The vertex set $V=\{1,2,\ldots,N\}$ of graph G corresponds to sensors and an ordered pair (v',v) of vertices belongs to the edge set E if there exists a communication link from sensor v' to sensor v. We denote the set of neighbors of v by $N(v)$. That is

$$N(v)=\{v'\in V:(v',v)\in E\},\quad v\in V.$$

We consider MAP estimation in M-ary hypothesis testing problems with conditionally independent observations. The observation vector is denoted by $Y=(Y_v : v\in V)$, where Y_v represents the measurements taken by sensor $v\in V$. Let $\{H_1,H_2,\ldots,H_M\}$ be a collection of M hypotheses with prior distribution π_0. The conditional probability density function of the observation vector Y under each hypothesis H_m, $m=1,2,\ldots,M,$ is denoted by $f_m(.)$. We shall assume that observations are conditionally independent given the true hypothesis. Specifically, for each realization $y=(y_v, v\in V)$ of observation vector Y

$$f_m(y)=\prod_{v\in V} f_{m,v}(y_v) \tag{1}$$

for marginal density $f_{m,v}(.)$. Let π denote the posterior distribution of the true hypothesis given the observations. Namely

$$\pi(H_m)=K\pi_0(H_m)\prod_{v\in V} f_{m,v}(y_v), \tag{2}$$

where K is a normalization constant that does not depend on *i*. Here both π and K depend on y but this dependence is suppressed in the notation for convenience.

Hypothesis H_m is a MAP estimate if

$$m\in\arg\max_j\left\{\pi_0(H_j)\prod_{v\in V} f_{j,v}(y_v)\right\}. \tag{3}$$

In many cases the prior distribution π_0 is unknown, and then the maximum likelihood (ML) estimate is used instead of MAP estimate. Hypothesis H_m is a ML estimate if

$$m\in\arg\max_j\left\{\prod_{v\in V} f_{j,v}(y_v)\right\}. \tag{4}$$

We shall consider distributed identification of a MAP/ML estimate in cases when a single decision maker having access to all observations is not available. More specifically, we focus on distributed algorithms in which each sensor collaborates with other sensors and thereby forms an estimate of the posterior distribution.

3. COLLABORATIVE FRAMEWORK USING DISTRIBUTED AVERAGING

In this section we introduce our approach using distributed averaging algorithms as a collaborative framework for the MAP estimation problem.

3.1 Distributed Averaging Approach

We are interested in distributed computation of the following quantity that depends on the measurements of N sensors

$$Q=\prod_{v\in V} f_{m,v}(y_v). \tag{5}$$

Let Q' be

$$Q'=\frac{1}{|V|}\log Q=\frac{1}{N}\sum_{v\in V}\log\left(f_{m,v}(y_v)\right)$$
$$\Rightarrow Q'=avg\left(\log\left(f_{m,v}(y_v)\right)\right)_{v\in V}. \tag{6}$$

where $|V|$ is the number of sensor nodes in the network and avg(.) denotes the averaging function.

Thanks to (6), we can utilize a distributed averaging algorithm to estimate Q', which is the average of log likelihood of every sensor's measurement, and this result will be used in computation of $Q=e^{NQ'}$ and then MAP/ML estimate. The averaging algorithm allows distributed calculation of sum of N log likelihood that live in N different nodes. This makes distributed event detection scalable with network size.

3.2 Distributed Averaging

Let $x_i(0)$ be a real-valued number (or a vector) assigned to node *i* at time *t=0* as node state, representing an observation of some type. The distributed averaging problem is to compute iteratively the average $(1/N)\sum_{i=1}^{N} x_i(0)$ at all nodes, using only local state and communication with its neighbor nodes.

We consider a time-varying network of n nodes, whose goal is to make available to each node the average value of the measurements of all nodes in the network, or at least a good approximation of it. At each time step *t*, every node *i* may perform an update operation of its estimate $x_i(t)$ of the overall average. This operation is linear, and relies only on the current average estimates from node *i* and from its neighbors. The update equation for node *i* at time *t* is

$$x_i(t+1)=w_{ii}(t)x_i(t)+\sum_{j\in N_i(t)} w_{ij}(t)x_j(t), \tag{7}$$

where $w_{ij}(t)$ are the weighting factors gathered in a weight matrix $\mathbf{W}(t)$ such that $\mathbf{x}(t+1) = \mathbf{W}(t)\mathbf{x}(t)$, where $x(t)=[x_1(t),...,x_n(t)]^T$ is the set of all estimations of all nodes at time t. The weights values are set according to averaging algorithms described later on, and $N_i(t)$ is the current active neighborhood of node i. $x_i(0)$ is the initial measurement at node i and $x_{ave} := 1^T x(0)/n = 1^T x(t)/n$ denotes the true average, where $1=[1,...,1]^T$ is the vector with all ones.

3.3 Different Averaging Strategies

According to [3], there are two main classes of distributed averaging algorithms: synchronous and asynchronous ones.

3.3.1 *Synchronous algorithms* or average consensus. All the nodes activate at each time slot t, communicate with their neighbors and update their current state.

3.3.1.1 *Uniform weights:* [5], [6]

$$w_{ij}(t)=\begin{cases}\alpha & \text{if } j\in N_i(t)\\ 1-\alpha\left|N_i(t)\right| & \text{if } i=j\\ 0 & \text{otherwise}\end{cases} \tag{8}$$

where α is a small enough constant for the algorithm to be stable, and $|\cdot|$ denotes cardinality.

3.3.1.2 *Metropolis weights:* [5]

$$w_{ij}(t)=\begin{cases}\dfrac{1}{1+\max\left\{\left|N_i(t)\right|,\left|N_j(t)\right|\right\}} & \text{if } j\in N_i(t)\\ 1-\sum\limits_{k\in N_i(t)} w_{ik}(t) & \text{if } i=j\\ 0 & \text{otherwise}\end{cases} \tag{9}$$

3.3.2 *Asynchronous algorithms* or gossip algorithms. At each time slot t, only one node activates. It performs an averaging process with one other node. In the most common gossip algorithm [7], the currently active node i choose one of its neighbors j and the both update their estimate x_i and x_j with their average $(x_i+x_j)/2$:

$$\begin{aligned} &w_{ij}(t)=w_{ji}(t)=w_{ii}(t)=w_{jj}(t)=1/2\\ &w_{kk}(t)=1 && \text{if } k\neq i,j\\ &w_{kl}(t)=0 && \text{on all other edges.}\end{aligned} \tag{10}$$

In geographic gossip, the information is routed through the network to allow non-neighboring nodes to average their values [8]. A possible extension could allow more than two nodes to average their value at each step [9]. In broadcast gossip [10], the currently active node i broadcasts its estimate value $x_i(t)$ to all neighbor nodes $N_i(t)$. Each node k in $N_i(t)$ uses the broadcasted value $x_i(t)$ to update its own estimate according to:

$$w_{jk}(t)=\begin{cases}1 & j\notin N_i(t), k=j\\ \gamma & j\in N_i(t), k=j\\ 1-\gamma & j\in N_i(t), k=i\\ 0 & \text{otherwise}\end{cases} \tag{11}$$

where $\gamma\in(0,1)$ is the mixing parameter of the algorithm.

Choosing the averaging strategy depends on many criteria. If we are interested in power consumption, we should use the broadcast model in which one node emits the same message to all its neighbors with only one transmission. In reliable networks, it is better to use asynchronous algorithms whereas unreliable networks work better with the synchronous algorithms. See [3] for more details about mathematical metrics to analyze and choose a suitable distributed averaging algorithm for your sensor network.

3.4 Scenario

Suppose that each node i has its own observation model and measurement Y_i of the observed event. To classify it among M hypotheses, the network performs following communication scheme to find out the most likely event:

1) Each node computes a vector of logarithm of conditional probability

$$x_i(0)=\log f_{m,i}(Y_i \mid H_m),\ m=1,...,M. \tag{12}$$

2) All nodes run the averaging algorithm to achieve average vector $\overline{x}$.
3) Each node uses a MAP estimator to find out the most likely event

$$m^* = \arg\max_m \left(\log\left(\pi_0\left(H_m\right)\right)+N\overline{x}[m]\right), \tag{13}$$

where $\overline{x}[m]$ is the *m-th* element of vector $\overline{x}$.

If we are only interested in ML estimate, then

$$m^* = \arg\max_m \left(\overline{x}[m]\right). \tag{14}$$

4. RESULTS

The distributed event detection method was simulated in a sensor network uniformly deployed in a square area. A lossless communication model was employed since the goal was to measure the convergence of the proposed technique. We ran 20 executions with 100 nodes and 10 different hypotheses. Figure 1 depicts convergence rate to the true MAP estimate of selected distributed averaging algorithms: uniform weights, Metropolis weights, and broadcast gossip. After some rounds of iteration, the network reaches a consensus about the MAP estimate. Figure 2 shows the mean square error (MSE), which has been normalized by the largest corresponding output, versus the number of radio transmissions.

5. CONCLUSION

This paper introduced a novel distributed event detection and in-network detection technique. It allows WSNs to detect specific events without having to first gather sensor observations and relay them back to a base station for processing. By reformulating the distributed event detection problem, we have more options to choose a suitable distributed averaging algorithm to solve the problem, depending on the synchronous or asynchronous communication model and other network conditions.

Collaboration among individual sensor nodes in the network is well-defined. Furthermore, the proposed technique is robust and scalable to network size.

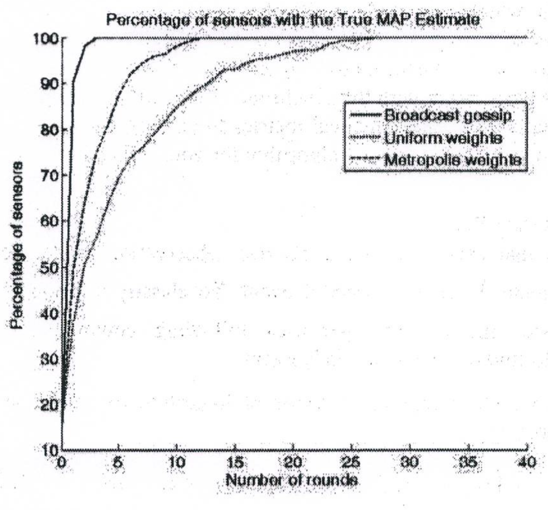

Figure 1. Rate of convergence to true MAP estimate.

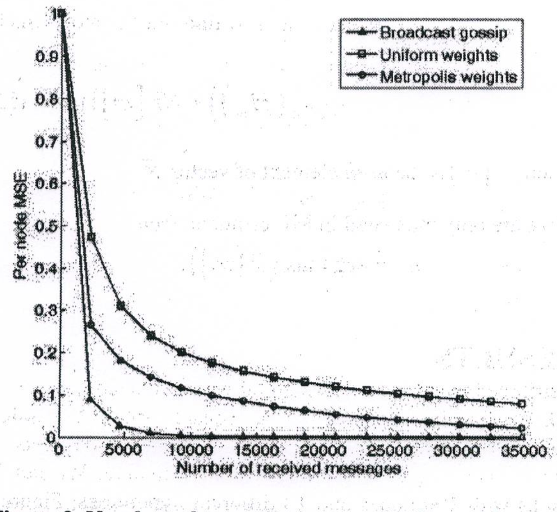

Figure 2. Number of transmission required to achieve a given MSE.

6. ACKNOWLEDGMENTS

This research was supported by the MKE (Ministry of Knowledge Economy), Korea, under the ITRC (Information Technology Research Center) support program supervised by the IITA(Institute of Information Technology Advancement)" (IITA-2009-(C1090-0902-0002)) and Was supported by the IT R&D program of MKE/KEIT, [10032105, Development of Realistic Multiverse Game Engine Technology]. This work also was supported by the Brain Korea 21 projects and Korea Science & Engineering Foundation (KOSEF) grant funded by the Korea government(MOST) (No. 2008-1342).

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