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Quality-Driven Congestion Control for Target Tracking in Wireless Sensor Networks

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Abstract

This paper describes initial research in addressing the challenges of managing quality of information for wireless sensor network target tracking with multiple missions of various priorities tracking multiple targets. We address the use of a distributed market-based mechanism to equalize the information value loss (that itself is a function of Quality of Information (QoI)) of tracked targets across multiple tracking missions while managing network congestion arising as a result of tracking. This includes considering missions' priorities and starvation of missions' data updates. In support of this approach, we define QoI as a function of the precision of position prediction of a tracked target and the loss of information value as the product of QoI and the priority of the mission tracking the target.

1. Introduction

Widely distributed deployments of wireless sensor networks (WSNs) consisting of small, intelligent, unattended and tetherless sensor nodes have sharply increased in recent times [1]. An important pervasive monitoring application of such a network is *distributed target tracking*. Although researched extensively in the past, this topic still have some important challenges unaddressed.

This particular work is motivated by a military usage scenario, although, as will be explained later, generalizations easily apply to other domains. In military settings, multiple target tracking missions (e.g., those executed by base command, infantry, or autonomous drones) with different priorities may require simultaneous access to a WSN given the scarcity of detection resources and the current threat level. In this paper, mission priority, which is assigned by some commander, reflects the commander's tolerance of the reduction of QoI, or, more specifically, to imprecision of target location. Hence, factors such as mission's intent, target's type and behavior may influence its priority. A problem arises if missions' separate targets travel within close proximity to each other, causing nearby sensors to broadcast updates and congest the path(s) from the targets to the sinks (missions). This is illustrated in Fig. 1, where targets A, B and C's close proximity causes congestion on nearby wireless links leading to the sink. To avoid collisions, we assume use of the STDMA protocol [5] in which only nodes that are more than two hops away might be assigned the same slot (indicated by same colors in Fig. 1). Both a mission's priority and QoI loss caused by the delay of packets with target position updates must be considered to properly determine bandwidth allocation at the point(s) of congestion. Major steps here involve (i) defining a quality metric appropriate for this usage scenario, and (ii) determining how to use it in bandwidth allocation in the considered usage scenario.

This paper describes initial research in addressing the afore-mentioned challenges. When network congestion arises, we use a distributed market-based mechanism to manage the QoI of tracked targets across multiple tracking missions according to their priorities. Specifically, the bandwidth allocated to missions at congested nodes equalizes the product of each mission's priority and QoI loss across all missions experiencing congestion. In support of this approach, we define QoI as a function of the precision of position prediction of a tracked target.

The paper proceeds as follows. Section 2 describes the background of this research topic. Section 3 discusses our concept of QoI as it relates to this

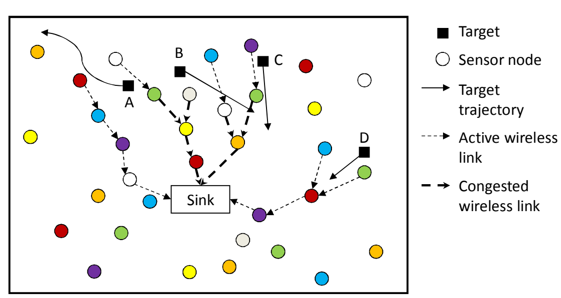

Figure 1. Wireless sensor network target tracking scenario causing network congestion.

particular problem. Section 4 describes our core algorithm relieving congestion and equalizing loss of information value for all missions. Section 5 describes an evaluation of the presented technique and Section 6 presents final thoughts and ideas for future works.

2. Background

Attempts to formalize the science of QoI within the context of WSNs are represented by some fledgling research activities. In [2], an investigation of the relationship between sensor sampling rates and the QoI metrics of timeliness and confidence is described and theoretical performance boundaries are established. In [11], the authors introduce a layered framework for performing QoI-centered performance evaluations of WSN deployments. The framework decomposes QoI analysis into three steps (reflective of typical sensor systems) and provides modularity in swapping different analysis and modeling approaches for detection tasks. In [4], the authors address the challenge of providing a flexible data stream meta-model for propagating QoI metrics from sensors to applications with low overhead as well as supporting the storage of QoI in relational databases.

Tracking moving objects using WSN technology is a well-established research area [8, 9, 13]. To the best of our knowledge, the intersection of QoI and target tracking has been largely represented by addressing tradeoffs between detection quality and energy consumption. For instance, in [7], the authors quantify the energy-quality tradeoffs under several different strategies for selectively activating sensors for target tracking and show that orders of magnitude savings in energy can be achieved with near-optimal tracking quality using a selective activation strategy. In [11], an adaptive framework is described that exploits an application's tolerance to erroneous sensor values by facilitating target tracking only at accuracy levels needed by the application and adjusting energy usage accordingly. In [3], *quality of monitoring* (QoM) is discussed, which is loosely similar to QoI. Here, the authors address performing low-energy tracking while maintaining a predefined level of QoM, even in the presence of noise and signal attenuation. Supporting this, a relay-area-based scheme is devised to determine the next sensor to activate when a target is moving while sustaining the required QoM, minimizing overall energy expenditure.

While these research efforts represent valuable contributions in managing quality-energy tradeoffs in target tracking, they assume use cases with single missions (or applications) and/or single targets. The work introduced here addresses these shortcomings by considering multiple missions and targets with different priorities. For this work, we assume that the energy management is addressed by the tracking algorithm itself and therefore is beyond the scope of this paper.

3. Quality and Value of Information

Following [10], we use the distributed target tracking algorithm in which a sensor that detects the target at the edge of its range computes its position, velocity and trajectory on site and without delay, and then reports this information to its neighbors and base station. The algorithm triggers this computation only when the target either enters or exits the sensing range of a sensor. This approach triggers the generation of a report packet at one sensor at a time and only if new information about the target is created. However, the frequency of the report is influenced by both the speed of the target and the density of the network deployment. The latter factor also impacts the precision of tracking. More details about this tracking algorithm are provided in [10].

We assume that a mission tracking a target measures the QoI that the WSN provides as a function of the uncertainty of the target's position. To reflect such a measure, we formally define QoI as

$$q_l(t) = r(t), \quad (1)$$

where $r(t)$ is the radius of a circle (or sphere in 3D) around the *predicted* position of the target at time t in which the target actually resides. In other words, $|x_p(t) - x_r(t)| \leq r(t)$, where $x_p(t)$ is the predicted position of the target at time t, and $x_r(t)$ is its real position at time t. An alternative formulation may consider the area in which the predicted position of the target may lay, yielding

$$q_q(t) = \pi \cdot r(t)^2 \quad (2)$$

For simplicity, we assume that packets carrying target information contain $x_r(t)$ and $v(t)$, the speed of the target at time of the measurement, t_m (i.e., we assume an ideal tracking algorithm). Assuming knowledge of the bound on the precision of the algorithm's tracking quality, it can easily be included in the described mechanism. Under this assumption, we would like to compute $r(t_m+\Delta t)$, assuming that the packet reporting the target's position and speed at time t_m is received up to time $t_m+\Delta t$. We compute this value under a model of *constant speed precision prediction*. In this model, we assume that the speed $v(t)$ reported at time t differs no more than $\Delta v=\alpha v(t)$ over the interval $[t, t+\Delta t]$ (physically, this corresponds to a reasonable solution in that there is a maximum acceleration for the object, or equivalently, a maximum force that can be applied to it.). Then, we have

$$r(t+\Delta t) = \left|v(t)\Delta t - \left(v(t)+\Delta v\right)\Delta t\right| = \alpha v(t)\Delta t\ . \quad (3)$$

Hence, $r(t)$ is linearly proportional to both $v(t)$ and the time delay of the packet in this model. It should be noted that in the most general case the speed precision prediction, α, should factor in both the imprecision of employed tracking algorithm and the unpredictability of the target's behavior.

To summarize here, we consider a model of QoI for target tracking that assumes constant speed precision prediction and yields the QoI measure as $q_l(t)= v(t)(t-t_m)$ for the linear case (Eq. (1)) and $q_q(t)= v(t)^2(t-t_m)^2$ for quadratic case (Eq. (2)), where t_m denotes the time of the last precise position update.

To rationally allocate the bandwidth in congestion, we will measure an overall information value loss caused by the delay of packets in congestion using the product of QoI, expressed as the uncertainty measure $q(t)$ and the subjective priority of the mission measure, p, assigned by the end user. Hence, our metric is defined as $m(t)=q(t)p$. Our goal is to equalize $m(t)$ among missions, assuming that the desired effect is to have equal loss of information values caused by congestion, which in case of equal priorities translates into equal loss of QoI for all missions. However, if one mission is valuable and the others are not, by assigning high priority to the valuable mission, the commander may effectively allocate the entire bandwidth to this mission. Hence, priority assignment can be viewed as a convenient tool to tune the system to yield the information that is most valuable to its users.

4. Prioritizing Packets in Congestion

We assume that to avoid transmission interference between nodes, the network uses a global spatial TDMA scheme in which each node uses one of n slots for transmission over the period t_c; hence, the packet transmission time is t_c/n.

Every time there is more than one packet to be forwarded for the current transmission slot allocated to a node, each packet computes its predicted loss of information value at the time of the end of the incoming transmission slot and enters it as its bid for that slot. The node, acting as an auctioneer, awards the slot to the highest bidder. Our goal is to forward packets in such a way that loss of information value for all participating missions is equalized in congestion and we will show that the described auction mechanisms achieves this goal. When there is no congestion, the QoI of each mission, as well as loss of information, is different as their packets experience different delays on their paths to destination and all might have different priorities and track targets moving with different speeds. It is only when congestion arises that we want to use equal information value loss as the guiding principle of packet selection for forwarding.

It should be noted that when a packet loses an auction and waits for the next one (when the next transmission slot for the node will be allocated) and the new packet for the given mission arrives at the node, the new packet overrides the current one in the queue of packets awaiting transmission. This is because according to the definition of a mission's QoI, the delivery of the current packet does not improve the mission's QoI, even if both packets are delivered together. Delivering the current packet before the incoming one results in lower QoI than delivering these packets in the reverse order. And finally delivering the current packet after the incoming one does not change the QoI and therefore is useless. As a result, in each auction, at most one packet from each mission will participate; for each mission this will be the most recently received packet.

We assume that each packet carries the following information: (i) time of the target's current position measurement, denoted as t_m, (ii) time of the target's position measurement of the previous packet for the same mission, denoted as $t_{m,p}$, (iii) the target's speed, denoted as v, and (iv) its mission priority, denoted as p. The processing of a packet bid at each node depends on whether it is the first packet of the mission reporting the target in the corresponding region that passes through this node to the destination or not.

In the case of the first packet, we also assume that each node knows its distance (in hops) to the destination and the average delay at each hop to the destination without congestion. Under the assumed routing protocol with global TDMA slot allocation, this delay is simply $(n/2+1)t_c/n$ because in addition to the transmission delay, the packet will wait on average half of the period t_c for the transmission slot. Hence, each node can compute the future expected delay of the packet on its way to the destination, which we denote as t_{up}. Likewise, for the first transmitted packet for the mission, we require that each forwarding node updates its cumulative actual delay from the source to the current node, which we denote as t_{down}. To accomplish this, the forwarding node simply adds to the received t_{down} value the difference between the time of ending the transmission of this packet to the next node, t_{dep}, and the actual time of packet arrival, t_{arr}. Hence, we have

$$t_{down}^{out} = t_{down}^{in} + t_{dep} - t_{arr}\,. \tag{4}$$

As a result, for each waiting packet of some mission i, we know its upstream delay t_{up} and downstream delay t_{down}, so we can compute its delay outside of the current node and denote it as t_o. Moreover, when the packet arrives at the node, its initial predicted delay from the time of measurement at the destination, t_p, is computed as the sum of t_o and the difference between the end of the

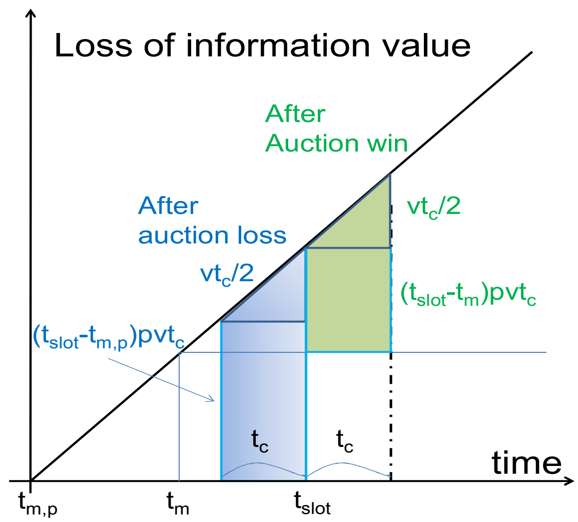

Figure 2. Loss of information value with the auction results

next transmission slot of this node, denoted as t_{next}, and the packet arrival time, t_{arr}, so

$$t_p = t_o + t_{next} - t_{arr}\,. \tag{5}$$

For the subsequent packets of the given mission passing through the given node, computation of the predicted delay from the time of measurement at the destination, t_p, is simpler. The initial value of t_p is the difference between the end of the next transmission slot of this node, t_{next} and the end of transmission of the previous packet of the same mission, denoted as t_{prev}. Indeed, if the upstream time, t_{up}, will remain the same for the current and previous packets, then the current packet, if selected for transmission in the incoming transmission slot, will arrive at the destination at time $t_{next}+t_{up}$, while the previous packet arrived at $t_{prev}+t_{up}$. Hence the delay between their arrivals at the destination will be

$$t_p = (t_{next}+t_{up}) - (t_{prev}+t_{up}) = t_{next} - t_{prev}\,. \tag{6}$$

In both cases, each time the packet (or its successors, if the packet is replaced by the next packet of the same mission before leaving the node) is not selected for transmission, its predicted delay is increased by the period t_c.

We will compute the predicted average loss of information value for the mission over the time of congestion as observed at the destination node (so after time t_{up} compared to the time at the current node). Hence, for each mission we will maintain the cumulative product of time and predicted information value loss, denoted as q_i, and the time, t_{start}, at which the congestion started. The computation of these two values proceeds as follows.

Consider the first packet that needs to compete for the incoming transmission slot for any mission. We assume that the congestion is observed at the destination after the first such packet arrives at the destination, so $t_{start}=t_{slot}+t_{up}$, where t_{slot} is the end of transmission for the first slot for which packets compete.

The cumulative time and predicted information value loss products for all missions participating in this first auction are set to 0.

For subsequent auctions, let $t_f=t_{up}+t_{slot}-t_{m,p}$ denote update delay at the base station caused by the previous auction. Then, if a packet loses the current auction, then at the end of the auctioned slot, the cumulative product of time and predicted information value loss of the corresponding mission is increased by

$$\Delta m_i^l = \int_{t_f}^{t_c+t_f} p_i v_i t\,dt = \left(t_f + \frac{t_c}{2}\right) p_i v_i t_c\,. \tag{7}$$

Otherwise, if the packet wins the auction, its increase of the product in each auction after the winning, regardless whether there is a packet of this mission waiting or not, but only until the first loss, is:

$$\Delta m_i^w = (t_{up} + t_{slot} - t_m + t_c/2)\,p_i v_i t_c\,. \tag{8}$$

Fig. 2 shows how the results of auction affect the loss of information value.

Knowing cumulative time and predicted information value loss product enables computation of the bid for the incoming time slot:

$$b_i = \frac{m_i + \Delta m_i^l}{t_{slot} + t_{up} - t_{start}}\,. \tag{9}$$

After the auction is decided, the winner's product is replaced by $m_i + \Delta m_i^w$ and the loser updates its product to $m_i + \Delta m_i^l$.

To demonstrate how easily this approach can be adopted to different definitions of QoI, we consider now QoI defined by a quadratic function of time as expressed in Eq. (2). Now, Eq. (7) becomes:

$$\Delta m_i^l = \int_{t_f}^{t_c+t_s} \pi p_i v_i^2 t^2\,dt = \left(\frac{t_c^2}{3} + t_f(t_c + t_f)\right) p_i v_i^2 t_c \tag{10}$$

Likewise, denoting $t_f^+ = t_{up} + t_{slot} - t_m$ the change at win becomes:

$$\Delta m_i^w = \left(\frac{t_c^2}{3} + t_f^+(t_c + t_f^+)\right) p_i v_i^2 t_c \tag{11}$$

The bid represents the current predicted average information value loss for the mission, assuming that the packet loses the current auction. Since we need to equalize information value loss among all missions, the packet for the mission with the highest predicted information value loss will be chosen for transmission.

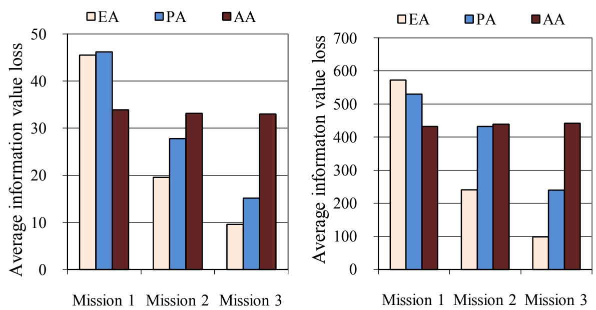

Figure 3. Actual average information value loss under the compared mechanisms, linear model (left part) and quadratic model (right part)

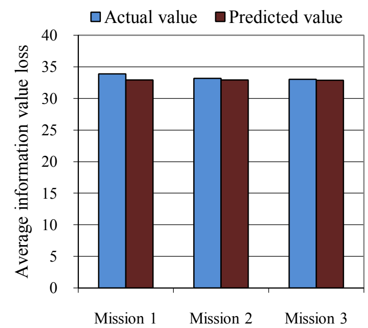

Figure 4. Actual and predicted average information value loss under auction mechanism, linear model.

It immediately follows from Eq. (7) and Eq. (8) that the auction winner information value loss grows slower after winning than it would after losing, as $t_m > t_{m,p}$.

It should be noted that q_i is predicted, not actual. For the first packet this is because t_{up} is predicted. For the subsequent packets, the computation of q_i assumes that the delay from the current node to the destination will be the same for the current packet as it was for the previous one. Hence, the achieved average information value loss in congestion may not be exactly the same for all missions (as will be shown in the evaluation section). However, the difference is small in practical cases since the congestion from the tracking update packets usually arises only in a single node between the sources of the packets and the destination.

5. Experiments

5.1 Evaluation Platform

We used NS-2 [6] to simulate our model, obtain its performance under some basic scenarios and demonstrate that our auction mechanism achieves its design goals. As mentioned before, we based our simulation on the Spatial TMDA protocol [5], which takes into account that sensor nodes are usually spread geographically, and therefore assigns the same time slots for transmission to nodes that cannot interfere with each other communications. As shown in Fig. 1, nodes that are more than two hops away might be assigned the same color (slot). Thus, by intrinsic design, STDMA protocols assure collision free communication at the cost of limited bandwidth at each sensor node. In the presented scenarios we assume that each node has one time slot out of the total of n=10 slots assigned for its transmissions, so each node has 1/10 of the bandwidth available for sending packets and its neighbors send packets in non-colliding slots.

The basic simulation setting is as follows. 50 sensor nodes are distributed uniformly randomly over a 500*m* x 500*m* field. There is a sink node where three missions receive their target information updates. We assume that constant traffic is generated by tracking the three moving targets in the sensor network and the three paths from the sensors tracking the object converge at a single node resulting in congestion. The sensor node reports the measurements 5 times per second sending packets of length 625 bytes. With this setting, the packet transmission time is same as the slot length. The radio transmission rate for all the nodes is configured at 250kb/s, the same as the transmission rate of MICAz motes. Meanwhile, we create three missions with priority values of 5, 2 and 1 respectively. Initially, we assume that all targets are moving with the same velocity set at 10m/s. All simulations were run for 400 seconds.

5.2 Results

To perform the evaluation, we compare our proposed approach to two other static scheduling mechanisms. The first static mechanism is to divide the bandwidth equally among all the missions, which will be referred to as EA (equal allocation). The second mechanism allows each mission to acquire access to transmission channel in a round robin manner and in each access to send the number of packets proportional to its priority, it is referred to as PA (proportional allocation) in the plots. Finally, AA denotes allocation via the auction mechanism introduced in this paper.

Fig. 3 shows the average information value loss of each mission for the three compared mechanisms under the linear and quadratic QoI models. As shown in Fig. 4, the average predicted information value loss of each mission is about equal to any other. As previously discussed, the actual average information value loss of missions might not be exactly equal since we use the predicted upstream delay t_{up} to calculate the bids. However, as shown in Fig. 4, the differences are rather small. Thus, our information value loss driven mechanism achieves nearly equal information value loss for multiple competing missions under congestion.

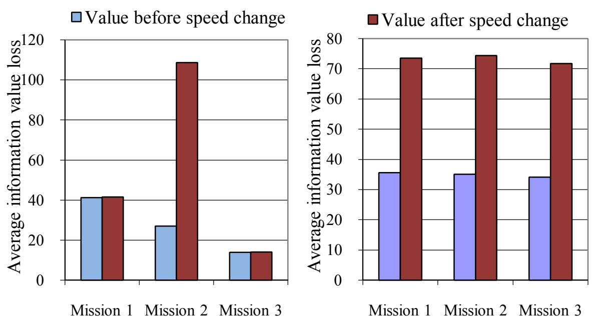

Figure 5. Impact of speed change on average information value loss under Proportional Allocation (PA, left part) and our Auction Allocation (AA, right part).

To demonstrate the adaptive nature of our proposed mechanism to changes in targets' velocities and missions' priorities, we compare our solution to PA. In the subsequent simulation scenario, the velocity of the target for mission 2 was changed from 10m/s to 40m/s. As shown in left part of Fig. 5, the actual average information value loss of mission 2 increased approximately four times after the speed change in PA. Moreover, Fig. 5 also illustrates that our auction mechanism kept the average information value loss in congestion nearly equal even after the change of speed.

6. Conclusion and Future Works

This paper describes early approaches and results. We plan to investigate other approaches to using information value loss including different auction techniques and considering other aspects of QoI.

In future work, we plan to explore a path selection algorithm which will use auction that the packet will invoke among potential forwarding nodes to select for transmission the node with the smallest predicted information value loss.

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