# Adaptive Object Tracking in a Sensor Network

Adrian Lopez Rodriguez
Northeastern University
Boston, MA 02115, USA
Email: a.lopezrodriguez@neu.edu

Milica Stojanovic
Northeastern University
Boston, MA 02115, USA
Email: millitsa@ece.neu.edu

***Abstract*—We address multiple object tracking in a system that has feedback from the fusion center to a wireless sensor network, where nodes transmit to the fusion center using random access. The feedback is used to adapt the sensing rate and, assuming that the sensors can move, to modify their positions. The variation in the position and the sensing rate of the sensors has the goal of providing higher accuracy of tracking and lower energy consumption. Simulations results are presented to demonstrate the benefits of feedback, which are notable when the network suffers from congestion. When the number of nodes is high the variable-rate approach is shown to provide a reduction of 2 dB in the location error and 44% less power consumed by the sensors. With mobile sensors, the accuracy of tracking is improved as the network is able to zoom in on the objects of interest.**

***Index Terms*—Wireless sensor networks, object tracking, adaptive tracking.**

## I. Introduction

Advancements in micro-electronics, wireless communications and sensor technology have made possible the evolution of Wireless Sensor Networks (WSNs). WSNs are formed by distributed, multi-functional sensor nodes that work in a collaborative manner. The sensors form an ad-hoc network through wireless communication, and they are used to collect data in order to monitor some phenomenon. The advantages over traditional sensing, that involves the use of one or few powerful sensors with centralized computation, include higher accuracy and greater coverage area.

The potential applications for WSNs are multiple. WSNs can be used for environmental applications, such as habitat monitoring or agriculture research. In addition, WSNs can be used in health monitoring topics, such as to control, in a non-invasive way, blood pressure, heart rate or concentration of oxygen in blood. WSNs also have military applications, such as detection of chemical or biological weapons or being part of command, control and communications. Underwater WSNs can be used to monitor water characteristics, to count animal life or to communicate with submarines and divers [1], [2].

One of the most studied applications for WSNs is tracking. The events to track range from moving bodies to changes in light, temperature or acoustics. A widely researched tracking method involves using the Received Signal Strength Indication (RSSI) [3], although alternative methods have also been studied, such as a cooperative vision-based system [4] or the use of binary proximity sensors to track the objects by sending only one bit of data per node [5].

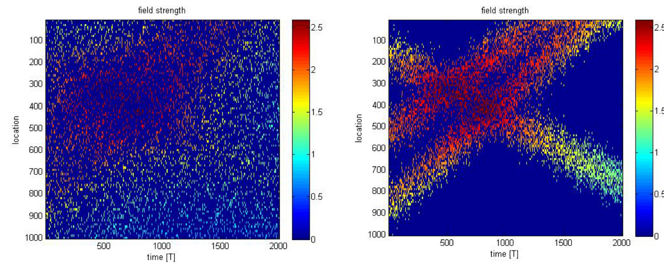
Energy efficiency is one of the most important factors in the study of tracking methods as the sensors are usually battery powered. In [6] the authors proposed a tracking method based on waking up the nodes only when an object is present, which is detected by sentry nodes that are always on. In [7] a cluster approach was proposed where the next sampling interval and the next working cluster are calculated by a cluster head using predictions from the current interval. In [8] a protocol to minimize the redundancy of the data sent and the transmission of low quality measurements was studied. The reduction of redundancy was achieved by having the sensors decide whether to send the object's estimated position (computed by triangulation using beacons from other sensors) to the cluster head depending on the position of neighboring nodes in the sensing range.

To improve the energy efficiency of the nodes and the accuracy of tracking, network congestion has to be controlled. Network congestion is more likely to appear in the upstream direction as a result of the high number of nodes communicating to a sink station. Congestion is especially critical in WSNs due to the limited computational power and wireless communication capabilities of the nodes, as well as the large network scale. There are two types of congestion: buffer overflow and link-level congestion. Buffer overflow causes loss of packets due to the limited buffer capacity in the nodes. Link-level congestion results in collisions when multiple sensor nodes try to use the channel at the same time, reducing the general transmission performance of the network and also its lifetime. Over the past years, researchers have studied several congestion detection and control methods [9], [10].

Radio or optical methods cannot be used underwater due to the high absorption and dispersion of electromagnetic waves. The underwater nodes are usually connected by wireless links based on acoustic communication. Some of the major challenges experienced in underwater acoustic networks are limited bandwidth, long propagation delays (acoustic signals propagate at 1500 m/s), fading and multi-path problems, Doppler effect and battery limitations. The battery limitation and the difficulty to recharge the batteries in the underwater environment makes energy efficiency critical. In addition, the communication issues of underwater acoustic networks makes congestion control necessary to save scarce resources [2].

In [11] adaptive object tracking was considered in a centralized topology where distributed nodes transmit to a Fusion Center (FC) using random access. The measurements were used in a stochastic gradient descent algorithm to track the objects present in the sensing area, which emit an exponentially decaying signature. In this paper, we extend that work by adding feedback by which the FC can instruct the sensors to increase/decrease their sampling rate, and, when mobile, to adjust their position. The goal in doing so is to improve both the accuracy of tracking and the energy efficiency of the system.

The paper is organized as follows. We present the system model in Section II. In Section III, we propose a variable-rate approach to the tracking problem. In Section IV, a scenario where the sensors can move is studied. In Section V, simulation results are presented to assess the performance of the system. Finally, we provide concluding remarks in Section VI.




(a) Fixed rate (b) Variable rate

Fig. 1. Recovered field at the FC as it evolves across a one-dimensional track over time in a fixed-rate scenario and a variable-rate scenario. The length of the track is 1000 m and the number of sensors is 100. There are three objects with unit amplitude and a decay rate of 0.002 $\mathrm{m}^{-1}$. The objects start at midpoints with velocities 3 m/s, -4 m/s and -5 m/s.

## II. System Model

We consider a one-dimensional track populated by $N$ sensors. We assume that each sensor knows its location and that the nodes are deployed homogeneously along the track, with a fixed separation $\Delta$ between them. We assume that there are $M$ objects in the sensing area, each characterized by an exponentially decaying signature $g(z) = Ae^{-\alpha|z|}$, where $A$ specifies the amplitude of the signal and $\alpha$ is the decay rate.

At time $t$ the sensor $i$ collects data from the field generated by the objects, $u_i(t) = \sum_{m=1}^{M} g(c_m - c_i)$, where $c_m$ is the position of the object $m$ and $c_i$ the position of the sensor $i$. The node encodes the measurement $u_i(t)$ in a data packet and sends it to the FC over a single-hop link. The sensing times of the sensor $i$ obey a continuous Poisson process with rate $\lambda_i$.

The FC collects the measurements during an observation window $T$. As a sensor may send more than one packet in a window, the FC discards all the repeated packets, the colliding packets and the erroneous packets due to communication noise. Following the treatment of [12], the rate of useful packets (those that did not collide and are not a repetition of the same packet) at the FC is modeled as a Poisson process with aggregate arrival rate

$$\lambda_{FC} = \frac{\sum_{i=1}^{N}(1 - e^{-p_s \lambda_i T})}{T} \tag{1}$$

where $p_s$ is the probability of successful reception of the packet at the FC. Assuming that a packet is successfully received if no other packet arrives during $(t - T_p, t + T_p)$ and if the packet is not erroneous due to communication noise, we have that $p_s = (1 - p_e)e^{-2\sum_{i=1}^{N}\lambda_i T_p}$, where $p_e$ is the probability of a packet being lost to communication noise

With the measurements gathered during $T$, the FC updates the estimates of the objects' locations, $\hat{c}_m$, and amplitudes, $A_m$, using a gradient descent approach.

The nodes in the network can be in four states: wake-up mode, reception mode, sleep mode, and transmission mode. The wake-up mode is a low-powered receiving state that is used when the nodes are awaiting an incoming transmission. In the wake-up mode it is possible to wake up a node by sending a special tone [13]. After the node has been woken up, its modem switches to the reception mode to receive the incoming transmission. The sleep mode is used when a node does not expect to receive a packet. In the sleep mode, the node does not sense the channel and no power is consumed. Finally, the node switches to a transmission mode when sending packets.

Feedback from the FC is introduced to the network as follows. The estimated positions of the objects are fed back from the FC to the nodes every $T_b$ seconds. Before transmitting the data, the FC sends a signal to wake the nodes up and transmits the information afterwards. The FC can adjust $T_b$ depending on the speed of the object being tracked. After transmission, the FC does not wait for any response. The sensors include the feedback information and a time-stamp when transmitting to the FC; hence, any sensor that does not receive the updated positions from the FC will eventually receive them from another node. In a system without feedback, the nodes stay in the sleep mode until they need to transmit.

The average power consumed by the sensor $i$ in a network without feedback is

$$P_{NF} = P_t \lambda_i T_p \tag{2}$$

where $P_t$ is the transmit power.

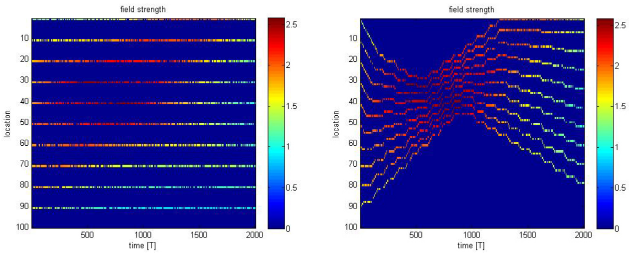
In a network with feedback, the power consumed by the sensor $i$ is

$$P_F = P_t \lambda_i T_p + P_w(1 - \lambda_i T_p) \tag{3}$$

where we are neglecting the power used to receive the packet from the FC. We assume that the number of broadcasts is much smaller than the number of transmissions, and that the power consumption due to the reception of the feedback information is negligible.

## III. Variable Transmission Rate

The feedback from the FC is used to instruct the nodes to vary their sensing rate. Rate-adaptation provides better accuracy of tracking and higher energy efficiency. With rate-adaptation, the nodes that sense a stronger signal, which is more useful for the tracking process, send more packets than the nodes that pick up a weaker signal, improving the accuracy




(a) Fixed sensors (b) Mobile sensors

Fig. 2. Recovered field at the FC as it evolves across a one-dimensional track over time in a fixed-sensors scenario and a mobile-sensors scenario. The length of the track is 100 m and the number of sensors is 10. There are three objects with unit amplitude and a decay rate of $0.002\ \mathrm{m}^{-1}$. The objects start at midpoints with velocities 0.3 m/s, -0.4 m/s and -0.5 m/s.

of the process. The reduction of the number of transmissions from sensors that are far from the objects also improves the power consumption of the nodes, provided that the power consumed in the wake-up mode is low enough.

Assuming that the sensors transmit at a rate $\lambda'$ initially, and that $d_i$ is the distance from the sensor $i$ to the closest object being tracked, we propose the following rate-adjustment strategy:

$$\lambda_i = \lambda' \cdot e^{-\dfrac{d_i^2}{2\sigma^2}} \tag{4}$$

where $\sigma$ is a parameter that determines the rate of adaptation (low values produce a fast reduction of the sensing rate depending on the distance of the sensor to the estimated object location).

The motivation for using (4) is to provide a gradual adaptation of the sensing rate depending on the distance to the estimated position of the objects, as the sensors closer to any of the objects receive a stronger signal that is more useful for tracking. To reduce transmissions from nodes that pick up a weaker signal, $\sigma$ is varied depending on (a) the decay rate of the signal emitted by the object and (b) the density of nodes.

Fig. 1 shows the field seen by the FC in each of the observation windows $T$. In the fixed-rate scenario, the sensors transmit packets with the same rate independently of the objects' position, making the number of collisions high due to the large amount of transmissions. In the variable-rate scenario only the closest sensors to the objects send data, hence the FC receives information from a small portion of the track. As the number of collisions is lower, the FC receives a higher number of packets from the sensors that pick up a stronger signal, which are more useful for the tracking process.

## IV. Mobile Sensors

Sensor mobility can improve the distribution of the nodes in a network, which in turn can result in better tracking and coverage, higher channel capacity, and longer network lifetime.

In our system model, the feedback from the FC can be used to instruct the sensors to change their positions, assuming that they can move. By moving the sensors, the density of nodes in a specific area can be augmented, thus lowering the tracking error as the signal that they sense is stronger. The ability to move the sensors is especially useful when the signal that the object emits decays fast and can thus be picked up only by close sensors. We assume that the sensors always have a perfect knowledge of their own position.

After receiving the feedback from the FC, each sensor moves at a fixed speed, $v_s$, to different positions around the estimated location of the object, effectively compressing the sensing area around the object by reducing the inter-node spacing $\Delta$. The nodes keep a homogeneous deployment, where all the nodes have the same separation between them. The sensors remain at their positions until the next update from the FC arrives.

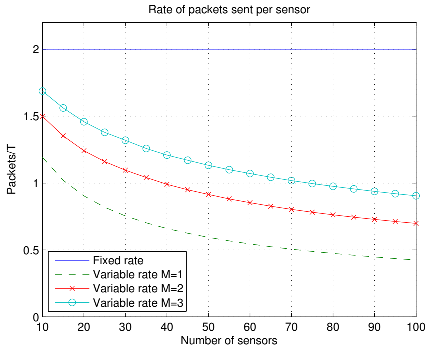
Fig. 2 shows the field seen by the FC in both the fixed-sensors scenario and the mobile-sensors scenario. In the mobile-sensors scenario we note the zoom-in effect: when the objects get closer together, the sensing area is effectively reduced; when they get further apart, the effective sensing area is enlarged. In the fixed-sensors approach, the FC receives weak measurements from some nodes, whereas in the mobile-sensors approach the measurements sent by all the nodes are stronger.

## V. Simulation Results

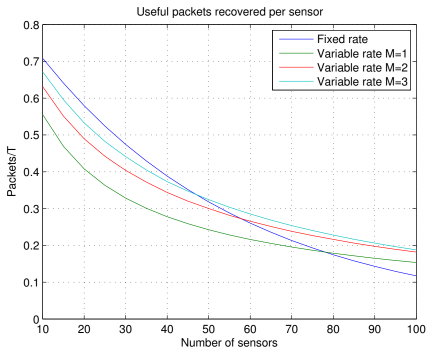
In the simulations performed, the effective SNR used is the one defined in [11], SNR $= \rho A^2/\sigma_w^2$, where $\sigma_w^2$ is the variance of the sensing noise, $\rho = \sum_{i\in\mathcal{R}_n} \dot{g}^2(c_i - c)$, $\mathcal{R}_n$ is the collection of useful measurements received in the collection interval $n$, $c$ is the position of the object and $c_i$ is the position of the sensor $i$. Assuming presence of a target at all times, and sufficient spatial resolution, $\rho \sim (p/\Delta)\int_{-\infty}^{+\infty}[\dot{g}(z)]^2 dz$ and $p$ is the probability that a sensor is contributing a useful measurement.

The power values in the simulation are taken in the range of the usual power consumption of the EvoLogics S2C R 48/7 Underwater Acoustic Modem [14], with $P_t = 18$ W (for 1000 m range, we assume that all the nodes use the same transmission power) and $P_w = 20$ mW.

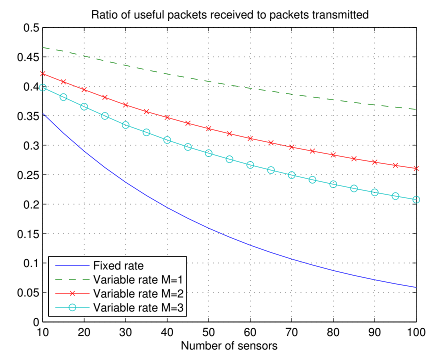
Fig. 3 shows the number of packets sent and the number of useful packets received (colliding packets and repeated packets are discarded) obtained in simulation using the variable-rate and fixed-rate approach. In this simulation, the objects are placed randomly along the track, and the initial rate $\lambda'$ is the same for all the cases considered. When the number of objects in the sensing area is reduced and the number of nodes is increased, the difference in the number of measurements sent in the two approaches is increased. When $N = 100$ and $M = 3$, the nodes send 55% fewer packets in the variable-rate scenario than in the fixed-rate scenario, and this difference is increased to 79% when $M = 1$. The lower number of transmissions translates into a higher ratio of non-colliding packets, making it easier to scale the sensing area by adding more nodes. The ratio of useful packets received at the FC to packets transmitted by the nodes is close to 0.05 in the fixed-rate scenario when $N = 100$, making the rate of useful packets




(a) Number of transmissions




(b) Useful packets received

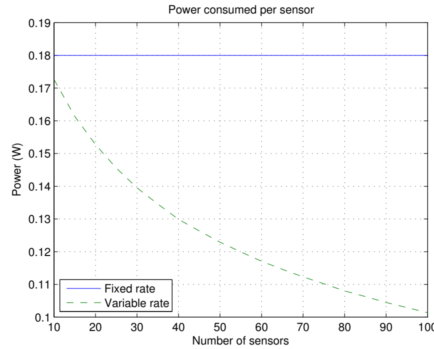



(c) Ratio of useful packets to packets transmitted

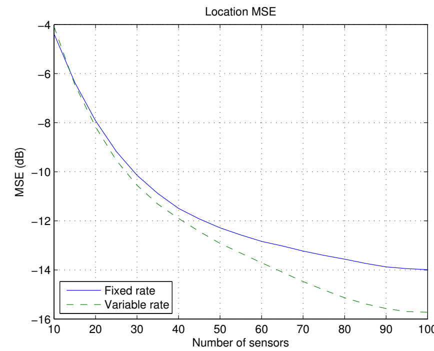
Fig. 3. Number of transmissions sent and useful packets received per sensor and $T$, and ratio of useful packets to packets transmitted in a fixed-rate scenario and a variable-rate scenario. The objects are placed randomly along a 100 m track. The simulations parameters are SNR= 0 dB, $\alpha = 0.02$ m$^{-1}$, $\lambda' =$ 20 packets/s, $T = 0.1$ s, $T_p = 0.5$ ms, $P_t = 18$ W, and $P_w = 10$ mW.

received at the FC, $\lambda_{FC}$, lower than in all of the variable-rate scenarios, despite the fact that more packets are transmitted.

To assess the performance of the rate-adaptation strategy in terms of location error and power consumption, we average the results from a single scenario over multiple noise realizations, random sensor activation and collisions. In the chosen scenario, three objects are placed in the midpoints of a 100 m track with velocities $0.3$ m/s, $-0.4$ m/s and $-0.5$ m/s. The squared location error is averaged over all targets and all collection intervals within the simulation time. Fig. 4 shows the results of the simulation. The variable-rate scenario has lower energy consumption than the fixed-rate scenario for all $N$. The power consumption difference is the result of reduced number of measurements sent per sensor. The difference in power is more noticeable for large $N$: with $N = 100$, the difference between the two scenarios is close to 80 mW per sensor. Furthermore, when $N \geq 15$, the error in the location estimates in the variable-rate approach is lower. With $N = 100$, the difference between the two approaches is almost 2 dB. This difference is a result of reduced network congestion: in the fixed-rate scenario, the packets sent by sensors far from the object are colliding with those sent by sensors that are closer. As the nodes that are closer measure a stronger signal, their data is more useful for the tracking process.



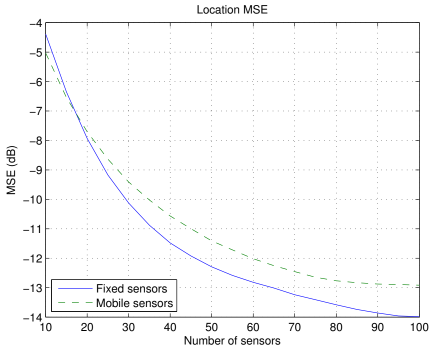

(a) Power consumption



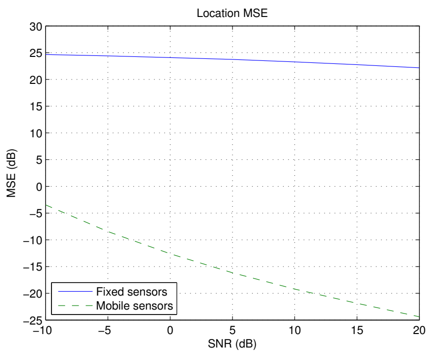

(b) Location MSE

Fig. 4. Power consumption and location MSE in a fixed-rate scenario and a variable-rate scenario. The simulations are performed with three objects placed at midpoints of a 100 m track with velocities 0.3 m/s, -0.4 m/s and -0.5 m/s. The simulations parameters are SNR= 0 dB, $\alpha = 0.02$ m$^{-1}$, $\lambda' =$ 20 packets/s, $T = 0.1$ s, $T_p = 0.5$ ms, $P_t = 18$ W, and $P_w = 10$ mW.

Next, we investigate the same scenario used in Fig. 4 to compare the performance of a network with static and mobile sensors. Fig. 5 shows that with $\alpha = 0.02$ m$^{-1}$ both approaches are able to track the object. The mobile-sensors approach performs better when the number of sensors is low, whereas the fixed-sensors approach provides higher accuracy when $N \geq 20$. When the density of nodes is low, the tracking process benefits from compressing the sensing area around the objects. When the density of sensors is high, the location MSE is higher in the mobile-sensors approach for two reasons. Firstly, as the density of nodes is already high, compressing the area is not as beneficial as when the number of nodes




(a) Location MSE versus number of sensors with $\alpha = 0.02\ \mathrm{m}^{-1}$ and SNR$= 0$ dB




(b) Location MSE versus SNR with $\alpha = 0.1\ \mathrm{m}^{-1}$ and $N = 10$

Fig. 5. Location MSE in a fixed-sensors scenario and a mobile-sensors scenario. The simulations are performed with three objects placed at midpoints of a 100 m track with velocities 0.3 m/s, -0.4 m/s and -0.5 m/s. The simulation parameters are $v_s = 1$ m/s, $\lambda' =$ 20 packets/s, $T = 0.1$ s, $T_p = 0.5$ ms .

is low. Secondly, in the mobile-sensors approach, the sensors may move further away from the actual positions of the objects when the estimates are not accurate enough due to collisions and sensing noise.

The performance improvement of the mobile-sensors approach is more noticeable with higher decay rates. Fig. 5 shows that objects that originally were not possible to pursue due to high exponential decay rate can be tracked using this approach. In the scenario with $\alpha = 0.1\ \mathrm{m}^{-1}$ the fixed-sensors approach is not able to track the position of the objects. The location MSE exceeds 20 dB for all the SNR cases considered. In this scenario, the mobile-sensors approach performs better than the fixed-sensors approach, as it is able to track the position of the objects.

## VI. Conclusion

The presented work has the intention to improve the energy efficiency and tracking capabilities of a wireless sensor network by using feedback information. The fusion center transmits the data and does not wait for any response from the node. The feedback information is used to adjust the transmission rate of the sensors or move them towards the objects of interest. The proposed variable-rate method has a lower power consumption than the fixed-rate approach when the number of sensors is sufficiently high due to the reduced number of transmissions. Moreover, when the number of sensors is increased, the localization error is also lower in the variable-rate scenario, as the number of useful packets received in the variable-rate scenario is higher despite the fact that fewer transmissions are made. In addition, mobile sensors provide lower tracking error in scenarios with low node density because the sensing area is compressed around the object being followed. Mobile sensors are also capable of following objects with high decay rate that are not possible to follow with fixed sensors.

Future research will focus on improved variable-rate solutions, in order to adapt the rate depending on the speed of the moving object. Future work will also extend the study of mobile sensors and the problems derived from its use, such as self-localization and collision avoidance problems.

## References

[1] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "A survey on sensor networks," *Communications magazine, IEEE*, vol. 40, no. 8, pp. 102–114, 2002.

[2] J. Heidemann, M. Stojanovic, and M. Zorzi, "Underwater sensor networks: applications, advances and challenges," *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, vol. 370, no. 1958, pp. 158–175, 2012.

[3] F. Viani, L. Lizzi, P. Rocca, M. Benedetti, M. Donelli, and A. Massa, "Object tracking through RSSI measurements in wireless sensor networks," *Electronics Letters*, vol. 44, no. 10, pp. 653–654, 2008.

[4] J. Sánchez-Matamoros, J.-d. Dios, and A. Ollero, "Cooperative localization and tracking with a camera-based WSN," in *Mechatronics, 2009. ICM 2009. IEEE International Conference on*. IEEE, 2009, pp. 1–6.

[5] W. Kim, K. Mechitov, J.-Y. Choi, and S. Ham, "On target tracking with binary proximity sensors," in *Information Processing in Sensor Networks, 2005. IPSN 2005. Fourth International Symposium on*. IEEE, 2005, pp. 301–308.

[6] T. He, P. Vicaire, T. Yan, L. Luo, L. Gu, G. Zhou, R. Stoleru, Q. Cao, J. A. Stankovic, and T. Abdelzaher, "Achieving real-time target tracking using wireless sensor networks," in *Real-Time and Embedded Technology and Applications Symposium, 2006. Proceedings of the 12th IEEE*. IEEE, 2006, pp. 37–48.

[7] J. Lin, W. Xiao, F. L. Lewis, and L. Xie, "Energy-efficient distributed adaptive multisensor scheduling for target tracking in wireless sensor networks," *Instrumentation and Measurement, IEEE Transactions on*, vol. 58, no. 6, pp. 1886–1896, 2009.

[8] E. Olule, G. Wang, M. Guo, and M. Dong, "Rare: An energy-efficient target tracking protocol for wireless sensor networks," in *Parallel Processing Workshops, 2007. ICPPW 2007. International Conference on*. IEEE, 2007, pp. 76–76.

[9] C.-Y. Wan, S. B. Eisenman, and A. T. Campbell, "Coda: congestion detection and avoidance in sensor networks," in *Proceedings of the 1st international conference on Embedded networked sensor systems*. ACM, 2003, pp. 266–279.

[10] B. Hull, K. Jamieson, and H. Balakrishnan, "Mitigating congestion in wireless sensor networks," in *Proceedings of the 2nd international conference on Embedded networked sensor systems*. ACM, 2004, pp. 134–147.

[11] K. Kerse, F. Fazel, and M. Stojanovic, "Target localization and tracking in a random access sensor network," in *Signals, Systems and Computers, 2013 Asilomar Conference on*. IEEE, 2013, pp. 103–107.

[12] F. Fazel, M. Fazel, and M. Stojanovic, "Random access compressed sensing over fading and noisy communication channels," *Wireless Communications, IEEE Transactions on*, vol. 12, no. 5, pp. 2114–2125, 2013.

[13] A. F. Harris, M. Stojanovic, and M. Zorzi, "Idle-time energy savings through wake-up modes in underwater acoustic networks," *Ad Hoc Networks*, vol. 7, no. 4, pp. 770–777, 2009.

[14] Evologics acoustic modems. [Online]. Available: http://www.evologics.de/