Energy-Quality Tradeoffs in Sensor Tracking: Selective Activation with Noisy Measurements

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ABSTRACT

Energy-efficient tracking of a target using a sensor network has received significant attention in recent research. Our earlier study on energy-quality tradeoffs in target tracking with binary sensors showed that optimal selective activation of sensor nodes based on prediction of the target's trajectory could achieve orders of magnitude savings in the energy expenditure over naive and random activation, while achieving almost the same tracking quality. In this paper, we consider a more realistic sensor model and extend the analysis of activation strategies to account for the presence of noise in sensor measurements. Our results confirm that the best quality of tracking that can be obtained with selective activation depends on the noise level in sensor measurements and that the optimal radius of activation depends on the noise level and the density of deployment. We also show how duty cycling with selective activation can be used to obtain flexible tradeoffs between the energy expenditure and quality of tracking.

Keywords: Sensor Networks, Target Tracking, Energy-Quality Tradeoffs, Noisy Sensors

1. INTRODUCTION

Advances in technology have made it possible to envision the ad-hoc deployment of large networks of wireless sensor devices for a range of intelligence gathering and monitoring applications.[1] One canonical application of wireless sensor networks is the tracking of a mobile target in the operational area.

As a target moves through the operational area, specific nodes may be activated for the sensing task. The particulars of the activation strategy can strongly influence both the energy usage (an important consideration in energy-starved sensor networks)as well as the quality of tracking. We study these tradeoffs here, in the context of a realistic sensor model that incorporates measurement noise.

Research work on target tracking with sensor networks has been motivated in large part by DARPA programs such as SensIT.[2] Some of the preliminary work on distributed algorithms in this area includes IDSQ,[3,4] location-centric tracking,[5,6] tracking algorithms based on pheromones and extended Kalman filter techniques[7,8] and tracking with mobile nodes.[9] Some attention has also been focused on deployment strategies for providing desirable tracking coverage.[10,11,12] There are also significant issues concerning multi-target tracking that are just beginning to be addressed.[13,14,15] The implementation and testing of a real distributed sensor network collaborative tracking algorithm in a military context is described by Moore *et al.*[16]

As in our earlier work,[17] our interest here is not in developing specific algorithms for tracking but in evaluating the energy-quality tradeoffs involved with different general activation strategies. In that earlier work,[17] in which we had considered simple ideal binary sensors (which yield a 1 or 0 depending on their observation of a target within sensing range), our results showed that selective activation of sensor nodes, based on prediction of the target trajectory could achieve orders of magnitude savings in energy expenditure. In this work, we consider a more realistic sensor model, whereby each node measures a distance-decayed signal from the target that is

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corrupted by measurement noise. In this context, we focus our attention on selective activation (SA) techniques, showing that the optimal activation parameters depend critically upon the noise level and density of deployment. We also show that duty cycling with selective activation can be used to flexibly effect different tradeoffs between the energy expenditure and tracking quality.

The rest of the paper is organized as follows. In section 2, we present our sensor and target location estimation models and describe the various activation strategies that we consider. We then describe our experiments and their results in section 3. We present our concluding comments in section 4.

2. MODEL AND METRICS

We consider a sensor network of n nodes deployed in an operational region with a single target moving within the region during the time interval $[0, T]$. At time instant t, if the target's position is $X(t) = \{x(t), y(t)\}$ and the sensors $S_i i = 1, 2, ...N$ are located at $X_i = \{x_i, y_i\}$, the signal strength from the target that is detected by sensor S_i is distance-decayed with noise, and is modelled as:

$$B_i(t) = \frac{B_o}{(1 + d_i(t)^\alpha)} + N_i \tag{1}$$

where B_o is the signal strength at the target's location, α the propagation decay exponent, $d_i(t)$ the instantaneous Euclidean distance between X_i and $X(t)$, and N_i the measurement noise at sensor i which is modelled as a Gaussian random variable with mean μ and unit variance.

We assume a signal strength-weighted technique for estimating the target position; i.e., if A is the index set of all *active* sensors at time t, the target is believed to be at location $X_b(t) = \{x_b(t), y_b(t)\}$, which is given by the following expression:

$$X_b(t) = \frac{\sum\limits_{i \in A} B_i(t) X_i}{\sum\limits_{i \in A} B_i(t)} \tag{2}$$

The metric we consider for the quality of target tracking is Q, the time average of the tracking error:

$$Q = \frac{1}{T} \int\limits_0^T \sqrt{(x(t) - x_b(t))^2 + (y(t) - y_b(t))^2} dt \tag{3}$$

We consider three general sensor activation strategies for target tracking: naive activation, randomized activation and selective activation. In naive activation (NA), all n sensors are switched on through the period of operation. In randomized activation (RA), at any instant of time each node is switched on with a probability p. Selective activation is considerably more sophisticated and requires the use of movement prediction mechanism. At each time step, all nodes within a radius R from the predicted location are turned on. For our model, we assume that R is chosen to be the average distance from the target at which the signal strength drops to a particular fraction f_1 of its original strength.

If $\mu = f_2 B_o$ be the mean value of the noise at each sensor, where $f_1 \in (0, 1)$ and $f_2 \in (0, 1)$, we have that

$$\begin{aligned} f_1 B_o &= \frac{B_o}{(1 + R^\alpha)} + f_2 B_o \\ \Rightarrow R &= \left(\frac{1}{f_1 - f_2} - 1 \right)^{\frac{1}{\alpha}} \end{aligned} \tag{4}$$

We can now easily characterize the energy expenditures of the three general activation strategies. In naive activation (NA), if the sensors are homogeneous and each have an energy expenditure $E_i = 1$ (normalized) units, the network has a total energy expenditure of $E_{NA} = n$ units. In randomized activation (RA), on average pN sensors are active and expend a total expected energy of $E_{RA} = pN$ units. For selective activation (SA), since at any point of time sensors within a circle of radius R are active, the expected energy expenditure with a density of deployment ρ would be $E_{SA} = \rho \pi R^2$.

Finally, we can perform duty-cycling with selective activation. For duty cycled activation, the activated sensor nodes in the network turn on and off for times t_{on} and t_{off} respectively with a period T_D. If used in conjunction with SA, the energy expended would be $E_{SADC} = \frac{t_{on}}{T_D} \rho \pi R^2$.

3. EXPERIMENTS AND RESULTS

We simulate a virtual large scale sensor network to evaluate the performance of the various tracking strategies. Sensors are placed on a 200 unit x 200 unit area with a default density $\rho = 1$ sensor/unit area (we also examine the impact of varying density in one of the experiments). The target signal strength at source is $B_o = 100$ units. To avoid edge effects in estimating uncertainty, our calculations are for trajectories in which the target stays away from the boundaries of the region. In the results presented, the target is assumed to follow a representative trajectory of the form $y(t) = Ax^B(t) + Csin Dx(t) + E$. We assume all sensors are homogeneous and add Gaussian noise with mean μ and unit variance to the signal measurements.

3.1. Naive Activation

We note that the signal detected by sensors far away from the target is dominated by noise. For instance, using $B_o = 100$ units, the actual signal measured by a sensor S_i which is distance $d_i = 30 units$ away would be close to 0.01 units. If the noise levels are substantially higher than this, then the weighted signal-strength approach can lead to increased tracking error. Hence, we set a threshold value for signal strength and values from sensors detecting a signal lower than this threshold value are not included in estimating the target's position. Figure 1 shows tracking error against the threshold signal strength for naive activation. The tracking error drops sharply initially as the threshold is increased since more of the noisy readings are being eliminated. On increasing the threshold further, the error increases slightly since some of the valid signals are being discarded. In our simulation, $B_{d=1}$=50 and for $\rho = 1$ there are very few sensors above the threshold and hence tracking is not possible for threshold values much greater than 50. For increasing values of the noise mean, the threshold for good tracking increases as expected. The energy expenditure is 40000 units in all cases.

3.2. Random Activation

Figure 2 shows how RA can achieve lower energy expenditure for a small tradeoff in the tracking error. Since random activation roughly corresponds to decreasing the density of sensor deployment, figure 2 indicates that if a moderate tracking error is acceptable, the density and hence total number of sensors can be reduced significantly. The energy expenditure is 10,000, 20,000 and 30,000 units for p= 0.25, 0.5 and 0.75 respectively.

3.3. Selective Activation

Figure 4 shows how the tracking error varies with energy for selective activation, with varying mean value of the sensor noise. The points correspond to different radii of activation R, (which roughly behaves like the inverse of the threshold in NA). Accordingly, as R is increased, the tracking error decreases since the likelihood of activating sensors close to the target increases. When R is very high, a lot of sensors far away from the target are activated. Their noisy readings and large numbers lead to erroneous estimation of the target position and increase in tracking error. The least tracking error possible increases with increasing noise mean. Figure 5 shows how the tracking error varies with energy for different activation radii and varying sensor density. Clearly, an optimal activation radius exists and is determined by the density of the sensor deployment and the noise levels in their readings. For the range of densities tested, we observe that increasing the density does not result in significant gains in terms of the tracking performance.

Figure 3 compares the performance of the three activation strategies. We observe that for optimal settings, SA can provide orders of magnitude energy savings with a tracking performance approaching that of NA. We also found through our experiments that on increasing the rate of prediction in SA, it matches the quality of tracking possible with NA in the limit.

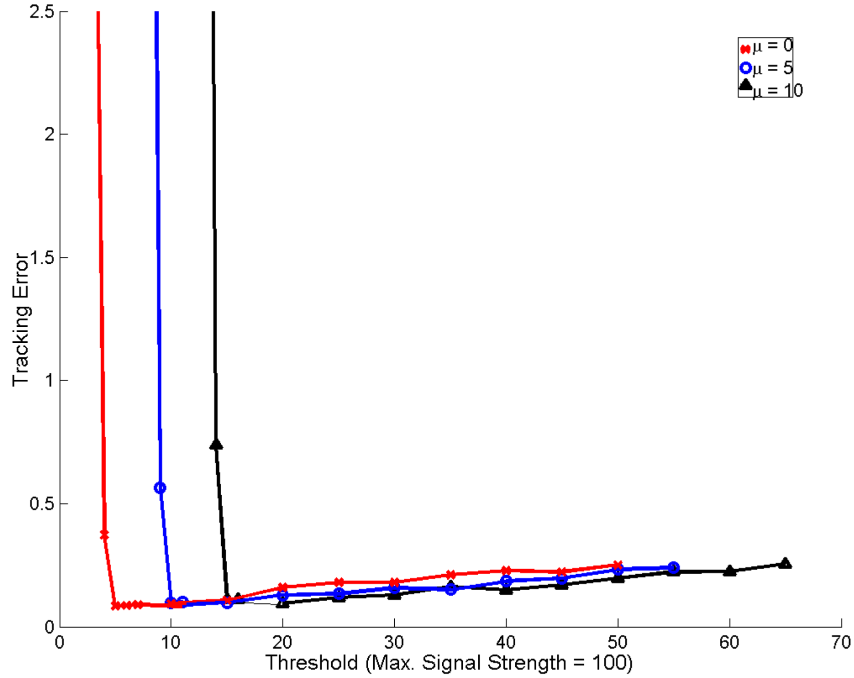

Figure 1. Tracking Error vs Threshold for varying Noise Mean: Naive Activation

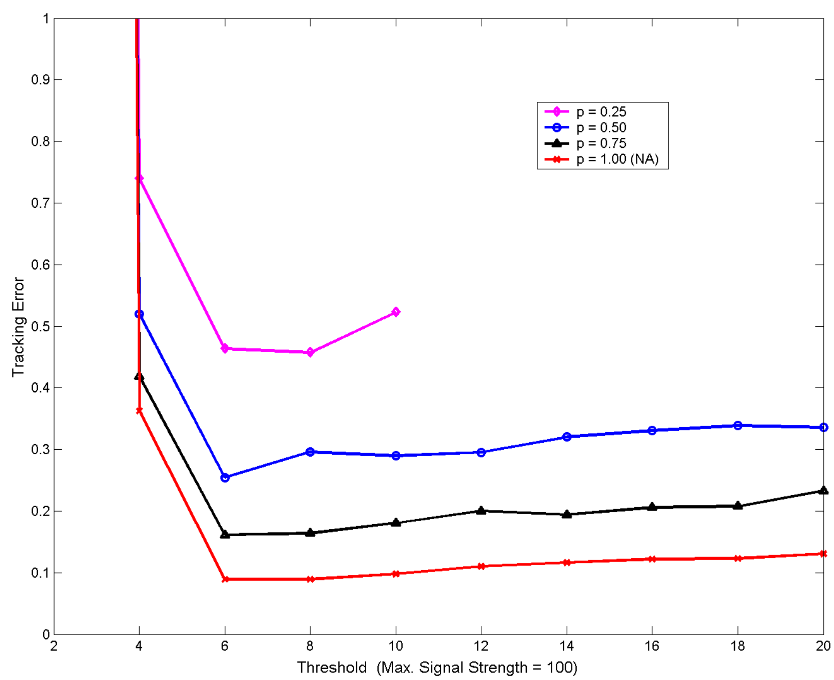

Figure 2. Tracking Error vs Threshold: Random Activation

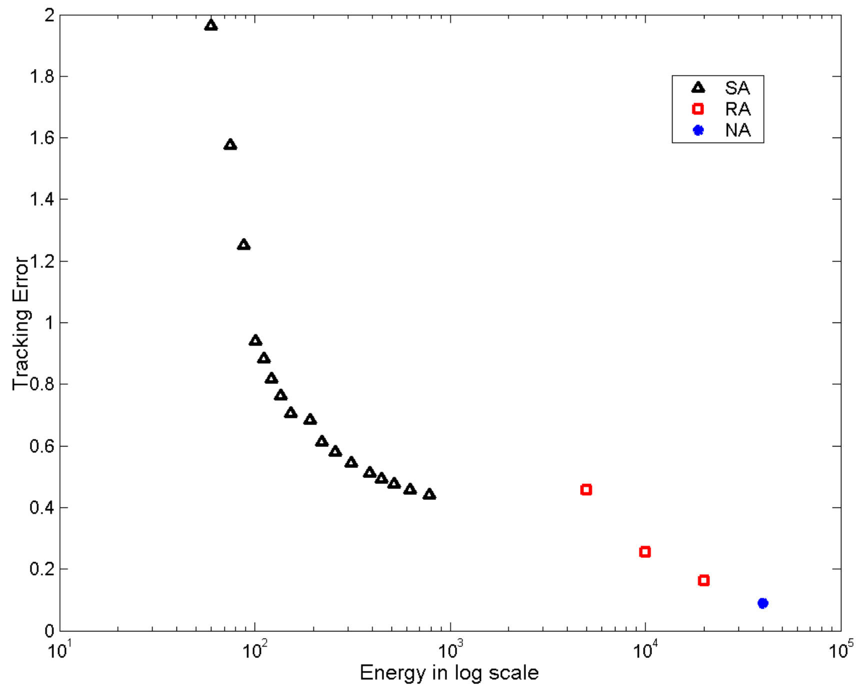

Figure 3. Comparison of the best tracking possible with various activation strategies

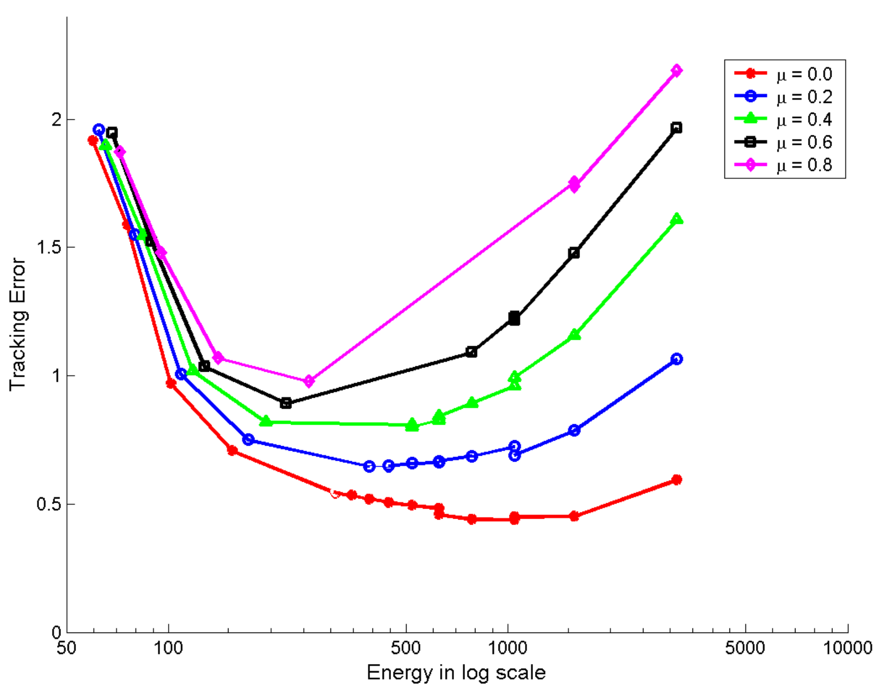

Figure 4. Tracking error vs Energy for varying noise levels: Selective Activation

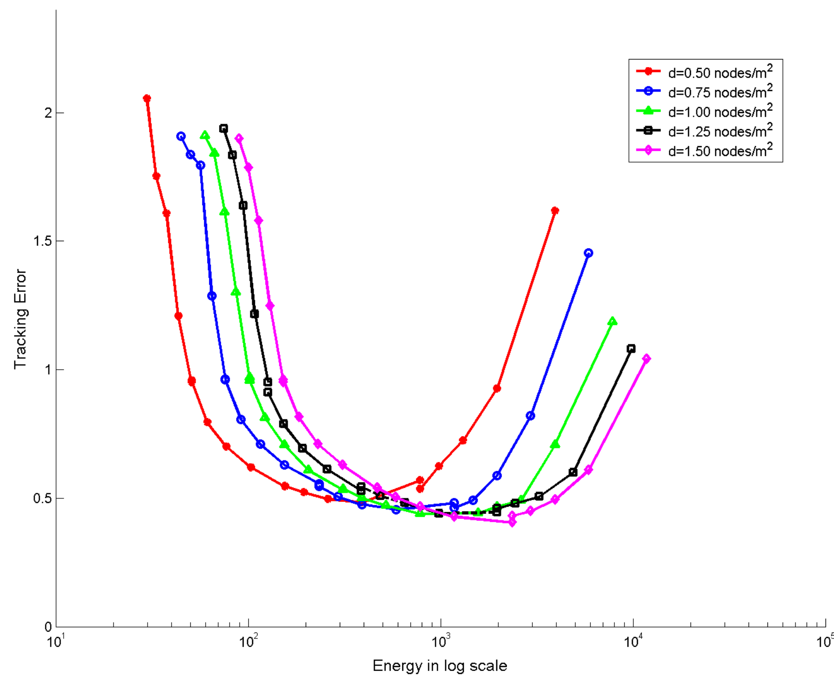

Figure 5. Tracking Error vs Energy for varying density of sensor deployment

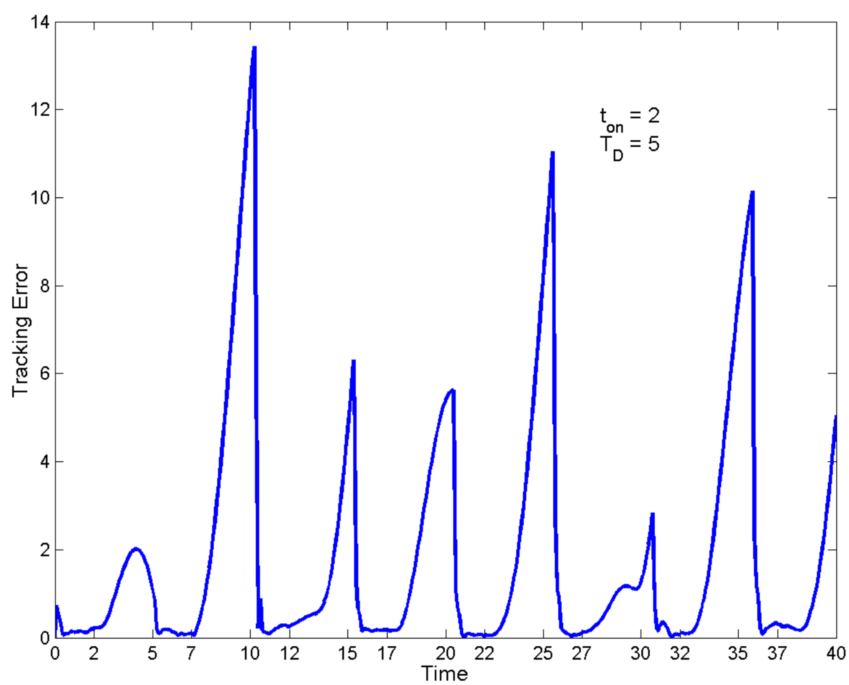

Figure 6. Instantaneous tracking error vs Time: Duty cycling over Selective Activation

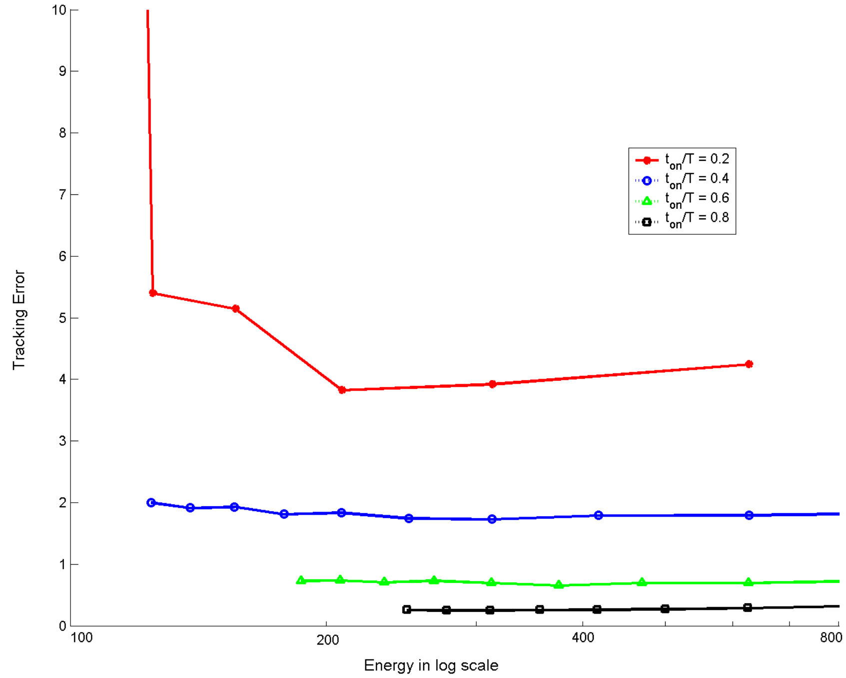

Figure 7. Tracking Error vs Energy for varying duty cycle: Duty cycling over Selective Activation

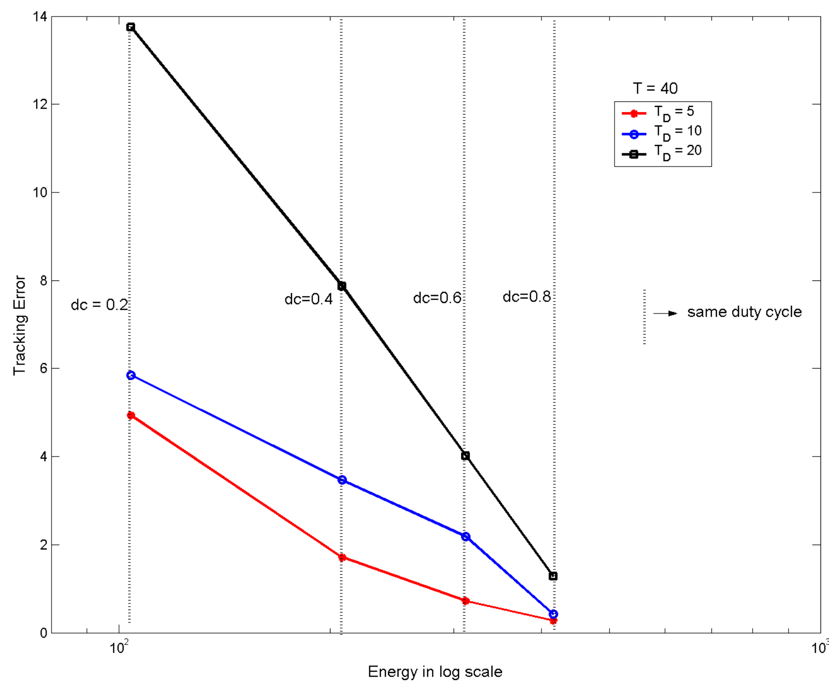

Figure 8. Tracking Error vs Energy for varying cycle period: Duty cycling over Selective Activation

3.4. Selective Activation with duty cycling (SADC)

Figure 6 shows the instantaneous tracking error vs time for SADC. The error is low during the on period and increases during the off period during which we use the trajectory in the on period and a linear predictor for an estimate of the target position.

Figure 7 shows the performance of SADC for varying duty cycle. We observe that by using a low duty cycle and choosing radius of activation carefully, energy savings can be obtained if a moderate tracking error is acceptable.

Finally, figure 8 compares the performance of SADC for varying time period T_D. For the same duty cycle, the tracking error increases with increase in T_D due to longer contiguous off periods. Depending on the speed at which the network can be switched on and off, SADC provides us a tuning knob to obtain various energy-quality tradeoffs by the careful choice of duty cycle and activation radius.

4. SUMMARY AND CONCLUSION

We extend the framework introduced in our earlier work[17] using a richer sensor model in which target detection is based on determining the strength of a decaying signal from the target, with the measurements being corrupted by noise. In the model we considered in this paper, the target position is estimated using the signal strength-weighted positions.

We showed that SA, with optimal settings, can provide orders of magnitude energy savings with a tracking performance approaching that of NA. We found that on increasing the rate of prediction in SA, it matches the quality of tracking possible with NA in the limit.

We found that there is an optimal signal strength threshold for NA and RA strategies. We also found that there is an optimal activation radius for SA that is determined by the density of the sensor deployment and the noise levels in their readings. Increasing the density does not appear to affect the tracking performance significantly and should be kept as low as possible. Depending on the speed at which the network can be switched on and off, we conclude that SADC provides us a knob to obtain various energy-quality tradeoffs by the careful choice of duty cycle and activation radius.

We are currently working to extend the simulation-based results presented here by developing mathematical models that would yield a better analytical understanding of the energy-quality tradeoffs in sensor networks.

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