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Target signature agnostic tracking with an ad-hoc network of omni-directional sensors

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ABSTRACT

Ad-hoc networks of simple, omni-directional sensors present an attractive solution to low-cost, easily deployable, fault tolerant target tracking systems. In this paper, we present a tracking algorithm that relies on a real time observation of the target power, received by multiple sensors. We remove target position dependency on the emitted target power by taking ratios of the power observed by different sensors, and apply the natural logarithm to effectively transform to another coordinate system. Further, we derive noise statistics in the transformed space and demonstrate that the observation in the new coordinates is linear in the presence of additive Gaussian noise. We also show how a typical dynamic model in Cartesian coordinates can be adapted to the new coordinate system. As a consequence, the problem of tracking target position with omni-directional sensors can be adapted to the conventional Kalman filter framework. We validate the proposed methodology through simulations under different noise, target movement, and sensor density conditions.

Keywords: Kalman filter, distributed target tracking, position estimation error, omni-directional sensors

1. INTRODUCTION

Ad-hoc constellations provide an attractive solution for deploying wireless sensor networks in different terrains or conditions. Tracking a target with an arbitrary signature, i.e., acoustic, seismic, electromagnetic, etc., has applications in different fields such as underwater acoustics, military surveillance, and security. In spite of the huge advances in sensor and communication technologies, power consumption and communication bandwidth very often limit the performance of the system. Typically, sensors are battery powered devices that get discarded once the power is depleted, making sensor cost a critical factor. As a consequence, omni-directional sensors often are simply designed, low-cost devices that can be deployed in large numbers and thus achieve fault tolerance by sheer redundancy. To further reduce the power consumption, thus enhancing the useful life of the device, only a minimum number of sensors are powered around the target. Additionally, to reduce the communication bandwidth and relax the synchronization requirements, one would use the target power as measured by the sensors surrounding the target. Unfortunately, a method that relies on estimating the received target power itself in order to estimate target position is unreliable. This is due to the fact that the target signature can be generated by various mechanisms and often is specifically designed to make it difficult to track or model. Furthermore, measured target power at the sensor is non-linearly dependent on the target position.

2. RELATED WORK

There are two parts of the tracking problem that need to be addressed: (1) How is the desired parameter (target position) observed? and (2) How is the a priori information regarding target movement behavior (target dynamic model) incorporated into target localization methodology?

A target emitting an arbitrary signature, i.e., acoustic, seismic, electromagnetic, etc., can be sensed by several omni-directional sensors as

$$Q^i(n)=\frac{S\left(n-\sqrt{\left(X^i-X(n)\right)^2+\left(Y^i-Y(n)\right)^2}\Big/cT\right)}{\Gamma\left(\sqrt{\left(X^i-X(n)\right)^2+\left(Y^i-Y(n)\right)^2}\right)}+N^i(n) \tag{1}$$

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where the superscript stands for sensor *ID*, n is the discrete time index, c is the propagation speed, and T is the sampling interval. The function $\Gamma(\ )$ describes the signal attenuation. For most tracking algorithms, the additive noise N_k is assumed Gaussian with zero mean and known variance. The sensors' positions although random are assumed to be known or estimated either by having a GPS circuit on every sensor or by having GSP circuits on selected sensors (beacons) and estimating the other sensor positions as described in [1].

The techniques that utilize direction of arrival (DOA) and time difference of arrival (TDOA) for target localization and tracking require that time series from at least two sensors are available at a time. The first method, (DOA), may use several omni-direction sensors that are bundled in a single processing unit. The bearing or direction of arrival is then estimated using narrow [2] or wide band techniques [3] based on the properties of the target signature. Time difference of arrival (TDOA) does not require sensors to be placed in a predetermined pattern and narrow or wide band signals can be treated similarly. In addition, frequency difference of arrival can be used [4] to estimate target velocity. Although the above methods are fairly well investigated and offer good performance, their practicality is limited due to the necessity to transmit the signal time series from at least half of the active sensors. For battery powered sensors, this affects adversely the operational time. Furthermore, sensing target position using its signature delay poses a limitation as system synchronization, sampling, and processing produce a time delay error that gets scaled up by signal propagation velocity to produce a position error. In consequence, we believe the above methods perform well for acoustic and seismic sensors but not for electromagnetic sources that require high accuracy. Another approach that reduces the communication bandwidth and relaxes the requirements for system synchronization is tracking by using target signal attenuation. In this case, the received signal strength (RSS) seems a natural choice as an indication for the source location. The authors in [5] rely on estimating the target power under the assumption that it is quasi static. While that may be true in some cases, it will not hold in the general case. In addition, countermeasures can be employed to craft a signature to disrupt possible tracking. In wireless communications networks, tracking the mobile terminal using RSSI is possible due to the fact that target power is precisely known. In [6], the authors utilize path attenuation measurements together with different propagation models to localize mobile terminals in an urban environment. The fact that the target signature power level affects the position estimation procedure forces the former to be estimated on the fly. Because the target signature can be man-made, the instantaneous power estimate cannot be modeled and/or refined by using a priori knowledge. The authors of [7] recognize the need to estimate the target power as the bottleneck of the target localization and propose a methodology that removes it from the estimation process. The latter is achieved by forming power ratios from different sensors and thus cancelling the contribution of the target power.

While the first part of the problem is selection of the function that maps the target position into a set of parameters that can be sensed with omni-directional sensors, the second part is how to connect to a typical target movement/dynamic model. Different measurement models are surveyed in [8] and while most of them are specified in a sensor specific coordinate system, the target dynamic models are traditionally specified in a Cartesian coordinate system. Carrying out the transition from the dynamic to the measurement coordinate system makes it possible to optimize the target position estimation. The final element of the problem is the framework that allows trade-off between target movement and observation uncertainty. Conventionally, in tracking the state of a stochastic but evolving system, two models are used: a system model and an observation model [9]. The system model specifies how the system evolves by defining the current state of the system as a sum of deterministic (based on previous state) and random (specifying the random and unknown excitation) parts. In a simplified way, the system model can be expressed as

$$X_{k+1} = A\left(X_k, W_k\right) \tag{2}$$

In the general case $A(\ )$ can be any function and W_k is the driving noise of the system. The system state X_k is observed in a noise environment through an observation function as

$$Z_k = H\left(X_k, V_k\right) \tag{3}$$

where V_k is the observation noise and $H(\ )$ can be any function in the general case. A Bayesian approach specifies a design procedure that yields a minimization of a certain cost function which is a function of the estimation error. The Bayesian approach reduces the procedure to estimating the conditional probability of X_k

$$p\left(X_k \mid Z_k, Z_{k-1}, \ldots, Z_0\right) \tag{4}$$

All the information needed to minimize any error cost function can be obtained from the conditional probability. As a consequence, the MSE estimate can be obtained by minimizing the mean square error and can be expressed as

$$X_{k\,mse} = E[X_k \mid Z_k, Z_{k-1}, ..., Z_0] \tag{5}$$

If such a system evolves and is observed in the above manner, the optimal *MSE* estimator is the Kalman filter. Therefore, in order for the Kalman filter to be the optimal MSE estimate, the following conditions should be met:

1. The functions *A( )* and *H( )* need to be linear functions of X_k, W_k, and V_k.

$$X_{k+1} = A_k X_k + W_k \tag{6}$$

$$Z_k = H_k X_k + V_k \tag{7}$$

2. The system (W_k) and observation (V_k) noises need to be jointly Gaussian with known mean and covariance.
3. The error covariance of the initial state X_0 should be known.

In this paper, we use a log-ratio transformation to remove dependency of the target signature instantaneous power. A new coordinate system for tracking is introduced and connected with a typical dynamic model. The observation noises are then propagated in the presented coordinate system and it is shown that under certain conditions, the observations are linear functions of the tracked parameters contaminated with additive Gaussian noise.

3. LOG-RATIO TRACKING

As indicated previously, the goal is to design a methodology with the following properties:

- Uses low-cost sensors
- Does not require large communication bandwidth for data transfer
- Does not require very precise sensor synchronization
- Is independent of the target signature since it is difficult to model in the general case
- Can be fit into the traditional Kalman filter framework

The proposed methodology is summarized in the following section.

3.1 Methodology outline

As indicated in [5], [6], and [7], using target power attenuation is an efficient approach for low-cost, robust tracking. The authors of [7] take it a step further and construct observations by taking ratios of the power observed by different sensors. We recognize the merit of this approach and continue in this direction by propagating observation noise covariance and deriving the dynamic model from a well known Cartesian constant velocity model. Our proposed approach can be summarized as follows:

1. Use the typical free space signal attenuation model, i.e., *v=1* (*n* is the discrete time index for the sensor sampling)

$$\Gamma\left(\sqrt{\left(X^i - X(n)\right)^2 + \left(Y^i - Y(n)\right)^2}\right) = \frac{1}{\left(\sqrt{\left(X^i - X(n)\right)^2 + \left(Y^i - Y(n)\right)^2}\right)^v} \tag{8}$$

2. Through power averaging at the sensor, obtain a power estimate (*k* is the discrete time index of the tracking system, and *P(k)* is the emitted target power)

$$Z^i(k) = \frac{P(k)}{\left(X^i - X(k)\right)^2 + \left(Y^i - Y(k)\right)^2} + V^i(k) = \frac{P(k)}{\left(d^i(k)\right)^2} + V^i(k) \tag{9}$$

3. Using four nodes, form three observations (independent *ij* pairs) as

$$Z^{ij}(k) = \ln\left(\frac{d^i(k)}{d^j(k)}\right) + V^{ij}(k) \tag{10}$$

(details regarding assumptions and noise propagation are described in the following paragraphs)

4. Form the Kalman filter state vector that includes log-distance ratios and their derivatives.
5. Derive corresponding system noise and observation noise statistics.
6. Derive the dynamic model in the new coordinate system using a constant velocity dynamic model in Cartesian coordinates.
7. At the output of the Kalman filter, obtain estimates of (superscript stands for node index).

$$\ln\left(\frac{d^1(k)}{d^2(k)}\right), \ln\left(\frac{d^2(k)}{d^3(k)}\right), \ln\left(\frac{d^3(k)}{d^4(k)}\right) \tag{11}$$

8. Obtain *XY* position from the log-distance ratios.

The target *XY* position can be obtained from the three distance ratios utilizing the Apollonius circle concept [10]. An Apollonius circle is a family of points which exhibit the following property: the ratio of the distances from any point on the Apollonius circle to two reference points is the same (shown in the Fig. 1).

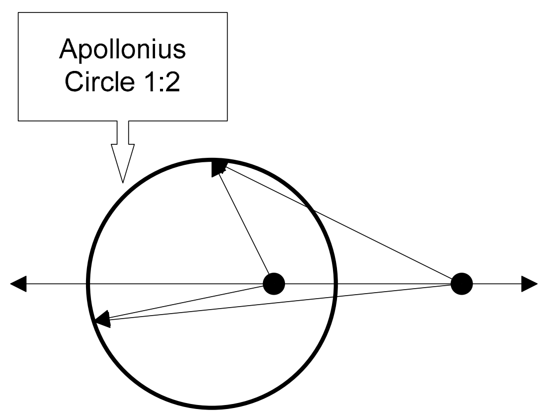

Figure 1. Apollonius Circle

The estimates of the three ratios define three circles where the potential target might be located. A *MSE* approach is used to obtain the target position in *XY* space from log-ratio space. Two important issues are described in the following sections: (1) Observation noise in the log-ratio space (see Section 3.2, "Observation model") and (2) Constant velocity dynamic model expansion to log-ratio space (see Section 3.3, "System/dynamic model"). The latter is a critical step to insure that both system and observation models are in the same coordinate system (and with known noise properties) and makes it possible to use the conventional Kalman filter as a simple and yet optimal tracker.

3.2 Observation model

Using the assumption in (8), the expression (1) becomes

$$Q^i(n) = \frac{S\left(n - \sqrt{\left(X^i - X(n)\right)^2 + \left(Y^i - Y(n)\right)^2} \Big/ cT\right)}{\sqrt{\left(X^i - X(n)\right)^2 + \left(Y^i - Y(n)\right)^2}} + N^i(n) \qquad (12)$$

The observation noise is assumed Gaussian with zero mean and variance σ^2 which is either known or estimated during operation. To obtain an estimate of instantaneous received power at the i^{-th} sensor, M samples are squared and averaged as

$$R^i(k) = \frac{1}{M} \sum_{n=kM}^{(k+1)M-1} \left(S\left(n - d^i(n) \big/ cT\right) d^i(n)^{-1} + N^i(n) \right)^2 \qquad (13)$$

Where k represents the index of power estimates and is effectively the rate of the Kalman filter while n is the discrete time index and represents the index of sensor samples. The signal delay term can be discarded if the product $d^i(n)/cT$ is much smaller than M. The expression then can be further simplified as

$$R^i(k) = \frac{1}{M} \sum_{n=kM}^{(k+1)M-1} \left(S(n)\, d^i(n)^{-1} + N^i(n) \right)^2 \qquad (14)$$

Separating the deterministic from the random components yields

$$R^i(k) = \frac{1}{M} \sum_{n=kM}^{(k+1)M-1} \left(S(n)\, d^i(n)^{-1} + N^i \right)^2 = P(k)\, d^i(k)^{-2} + U^i(k) \qquad (15)$$

where

$$P(k) = \frac{1}{M} \sum_{n=kM}^{(k+1)M-1} S(n)^2 \qquad (16)$$

and the target travelled distance during the time interval MT is sufficiently small when compared to the desired position estimation accuracy. As M becomes large, the sum of all noise components grouped as U_k approaches Gaussian distribution.

$$U^i(k) \sim \mathrm{N}\left(\sigma^2, \left(4P(k)\, d^i(k)^{-2} \sigma^2 + 2\sigma^4\right) / M\right) \qquad (17)$$

For notation purposes, the sensor index is omitted and the time index is shown as a subscript. Removing the noise mean (which is known) and taking the logarithm forms the new observation function

$$Z_k = \ln\left(R_k - \sigma^2\right) = \ln\left(P_k\, d_k^{-2}\right) + \ln\left(\frac{P_k\, d_k^{-2} + U_k - \sigma^2}{P_k\, d_k^{-2}}\right) = \\ = \ln\left(P_k\, d_k^{-2}\right) + \ln\left(1 + V_k\right) \qquad (18)$$

where

$$V_k \sim \mathrm{N}\left(0, \frac{\left(4P_k\, d_k^{-2} \sigma^2 + 2\sigma^4\right)/M}{P_k^2 d_k^{-4}}\right) \qquad (19)$$

Using the notation

$$SNR_k = \frac{P_k d_k^{-2}}{\sigma^2} \qquad (20)$$

and substituting in the above equation yields

$$Z_k = \ln\left(P_k\, d_k^{-2}\right) + \ln\left(1+V_k\right) \quad V_k \sim \mathrm{N}\left(0, \frac{4SNR_k + 2}{SNR_k^2 M}\right) \tag{21}$$

If SNR_k , which is signal-to-noise ratio at the sensor, is at least *0dB*(Assumption #1 – *SNR>0dB*), the noise variance becomes $\approx 0.03 << 1$ so the following approximation can be used:

$$\ln\left(1+x\right) = x \quad if \quad x << 1 \tag{22}$$

The observation then can be simplified as

$$Z_k = \ln(P_k) - 2\ln(d_k) + V_k \quad V_k \sim \mathrm{N}\left(0, \frac{4SNR_k + 2}{SNR_k^2 M}\right) \tag{23}$$

Forming a new observation using two nodes yields

$$Z_k^{ij} = \left(Z_k^i - Z_k^j\right)/2 = \ln\left(\frac{d_k^j}{d_k^i}\right) + V^{ij}{}_k \quad V^{ij}{}_k \sim \mathrm{N}\left(0, \frac{SNR^i{}_k + 1/2}{SNR^{i2}_k M} + \frac{SNR^j{}_k + 1/2}{SNR^{j2}_k M}\right) \tag{24}$$

The *SNR* at the sensor can be approximated as

$$SNR_k^i = \frac{P_k\, d^{i^{-2}}}{\sigma^2} \approx \frac{P_k\, d^{i^{-2}} + U_k^i - \sigma^2}{\sigma^2} = \frac{R_k^i - \sigma^2}{\sigma^2} \tag{25}$$

3.3 System/dynamic model

The system model is described in a two-dimensional Cartesian *XY* space although generalization to *XYZ* space is easily done. A survey of dynamic models is provided in [11] and, while there are more sophisticated models, the constant velocity model presents a viable solution that is relatively independent of the target type. The constant velocity model is used to describe target movement in Cartesian coordinates and to derive the log-ratio system model. The constant velocity model can be described as (for simplicity only one component, i.e., *X*, is used)

$$\begin{bmatrix} X_{k+1} \\ \dot{X}_{k+1} \end{bmatrix} = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix} \begin{bmatrix} X_k \\ \dot{X}_k \end{bmatrix} + \begin{bmatrix} \frac{\Delta t^2}{2} \\ \Delta t \end{bmatrix} W_k \tag{26}$$

First, it needs to be pointed out that the selection of the axis orientation is irrelevant. The axes even need not be orthogonal if the correlation between the driving noise projections are taken into account. Moreover, the individual axis origins need not be the same and the number of projections is not limited by the dimensionality of the space covered. The axis need not be stationary as long as they are well defined. With that in mind the axes are chosen such that:

- There is one axis per sensor (four sensors are used for tracking).
- The axis origin is the sensor position.
- The axis vector is the vector connecting the sensor to the target.

If the axis is chosen in the above fashion, the axis projection becomes the distance between the target and the sensor. If the same axis is used for the subsequent projection (*k^{th} +1*), the actual projection approaches the distance at time *k+1* if the traveled distance between time *k* and time *k+1* is much smaller than the distance to the node (Assumption #2). Since the maximal target velocity is determined by the type of the target and the sampling interval is controlled by the design, this condition is easily achieved (and controlled). The geometry described above is shown in Fig. 2.

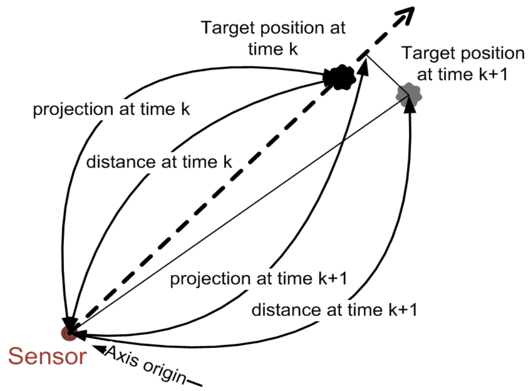

Figure 2. Axis transformation

The system model from (26) then becomes

$$\left| \begin{array}{l} d_{k+1} = d_k + \Delta t \, \dot{d}_k + \dfrac{\Delta t^2}{2} W_k \\ \dot{d}_{k+1} = \dot{d}_k + \Delta t \, W_k \end{array} \right. \tag{27}$$

where the matrix representation of the model is substituted with two equations and is subject to the assumption

$$d_k >> \Delta t \, \dot{d}_k + \frac{\Delta t^2}{2} W_k \tag{28}$$

Using the following notations

$$Ld_k = \ln\left(d_k\right) \quad , \quad \dot{L} d_k = \frac{\partial Ld_k}{\partial k} = \frac{\dot{d}_k}{d_k} \tag{29}$$

the natural logarithm is applied to the first equation in (27)

$$Ld_{k+1} = Ld_k + \ln\left(1 + \frac{\Delta t \, \dot{d}_k + \frac{\Delta t^2}{2} W_k}{d_k} \right) \tag{30}$$

Using the assumption from (28) and the approximation from (22), the first equation in (27) can be written as

$$Ld_{k+1} = Ld_k + \frac{\Delta t \, \dot{d}_k}{d_k} + \frac{\Delta t^2}{2} \frac{W_k}{d_k} = Ld_k + \Delta t \, L\dot{d}_k + \frac{\Delta t^2}{2} \frac{W_k}{d_k} \tag{31}$$

Again using the assumption from (28), the second equation in (27) can be written as

$$\frac{\dot{d}_{k+1}}{d_{k+1}} = \frac{\dot{d}_k}{d_k} + \Delta t \frac{W_k}{d_k} \tag{32}$$

which using notation from (29) is

$$L\dot{d}_{k+1} = \dot{L} d_k + \Delta t \frac{W_k}{d_k} \tag{33}$$

The final equation of the log-distance system model then can be written as

$$\begin{bmatrix} L^i d_{k+1} \\ \dot{L}^i d_{k+1} \end{bmatrix} = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix} \begin{bmatrix} L^i d_k \\ \dot{L}^i d_k \end{bmatrix} + \begin{bmatrix} \frac{\Delta t^2}{2} \\ \Delta t \end{bmatrix} \frac{W^i{}_k}{d_k^i} \tag{34}$$

3.4 System noise covariance computation in log-ratio space

So far it has been shown that from the constant velocity *XY* model one can transition to a similar constant velocity log-distance model and the individual noise components can be derived from the *XY* model noise components. What remains is to show the computation of the noise cross-correlation in order to construct the full system noise covariance matrix. The latter can be obtained by accounting for the fact that the projection axis may not be orthogonal.

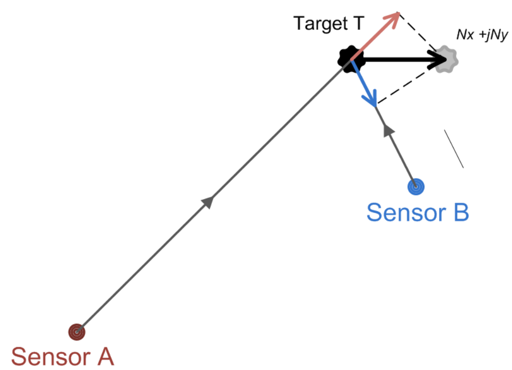

Figure 3. Noise projection on arbitrary axis

The dark black arrow in Fig. 3 corresponds to the noisy component of the system evolution. This vector can be position, velocity, or acceleration, based on the assumed model. In the Cartesian coordinate system, the system driving noise is specified as having *X* and *Y* components on arbitrary but orthogonal axes, each of which is zero mean Gaussian with variance σ^2. The covariance matrix of the projected noise components (in blue and red) can be specified as

$$Cov\left[W^A W^B\right] = \sigma^2 \begin{bmatrix} 1 & \vec{BT} \bullet \vec{AT} \\ \vec{BT} \bullet \vec{AT} & 1 \end{bmatrix} \tag{35}$$

where *AT* and *BT* are unit vectors connecting sensors A and B respectively to the target and • stands for the dot product. If the following notations are used

$$Ld_k^{ij} = Ld_k^i - Ld_k^j \quad , \quad \dot{L} d_k^{ij} = \dot{L} d_k^i - \dot{L} d_k^j \tag{36}$$

the system model can be described as

$$
\begin{bmatrix} Ld_{k+1}^{12} \\ \dot{L}d_{k+1}^{12} \\ Ld_{k+1}^{23} \\ \dot{L}d_{k+1}^{23} \\ Ld_{k+1}^{34} \\ \dot{L}d_{k+1}^{34} \end{bmatrix} = \begin{bmatrix} 1 & \Delta t & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & \Delta t & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & \Delta t \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} Ld_{k}^{12} \\ \dot{L}d_{k}^{12} \\ Ld_{k}^{23} \\ \dot{L}d_{k}^{23} \\ Ld_{k}^{34} \\ \dot{L}d_{k}^{34} \end{bmatrix} + \begin{bmatrix} \begin{bmatrix} \frac{\Delta t^2}{2} \\ \Delta t \end{bmatrix} \left(\frac{W_k^1}{d_k^1} - \frac{W_k^2}{d_k^2} \right) \\ \begin{bmatrix} \frac{\Delta t^2}{2} \\ \Delta t \end{bmatrix} \left(\frac{W_k^2}{d_k^2} - \frac{W_k^3}{d_k^3} \right) \\ \begin{bmatrix} \frac{\Delta t^2}{2} \\ \Delta t \end{bmatrix} \left(\frac{W_k^3}{d_k^3} - \frac{W_k^4}{d_k^4} \right) \end{bmatrix} \quad (37)
$$

with noise covariance specified in (35).

4. SIMULATION RESULTS

4.1 Simulation setup

To verify the performance of the log-ratio tracker described above, a simulation with the following properties was constructed:

- The target emits a low pass signature with a maximum frequency of 10 kHz and sensors sample at 20 kHz.
- Noise observed from sensors is Gaussian with zero mean and known variance.
- Only 4 sensors are active (powered) at a given time.
- A window of *M=200* samples is used to obtain a power estimate through averaging at the sensor.
- Sensor synchronization error is much smaller than 1/250=4ms.
- The constellation of sensors is formed by adding Gaussian noise to a square grid at a distance of *D* meters.
- As the target is being detected through the sensor field, the closest four sensors are powered (considered active).

To verify performance under different conditions, a set of simulations was formed with three dimensions:

- Target velocity – 3 values of target average velocity – 2, 10, and 20 m/h
- Sensor distance *D* – side of square grid – 10 and 40 m
- For type of condition, a sweep of ten SNR points (between 0 and 9 dB) was evaluated.

The SNR is specified as the received signal power at the sensor over the noise power at the worst possible location. For an approximately rectangular sensor grid like the one used, the SNR is defined as the signal power at the sensor while target is at distance $\sqrt{2}D$ divided by the noise power.

4.2 Simulation results

An example of tracking at lowest *SNR*, i.e., *0 dB*, with sensor grid of *10 m*, is shown in Fig. 4. The black circle indicates the target starting point while the color diamonds indicate sensor positions. The blue and the red lines show the original and estimated target positions, respectively. In order to provide more uniform means for comparison, the same target trajectory was used in all three cases and was scaled to produce average speeds of 2, 10, and 20 m/h. As the target moves through the sensor field and is tracked, the four sensors closest to the target are powered on. The tracking algorithm switches the tracking sensor group based on the target velocity and sensor grid density, i.e., a faster moving target causes more frequent active sensor group changes.

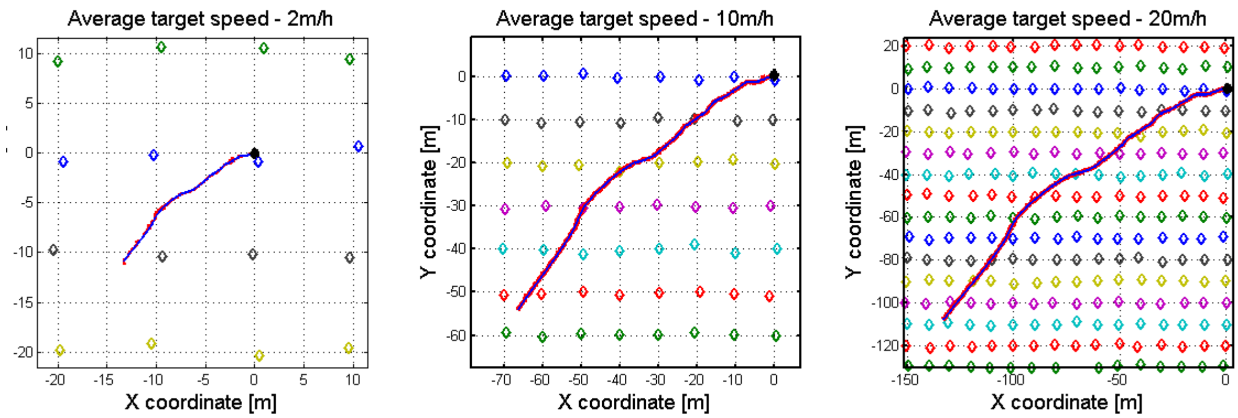

Figure 4. Target tracking - 10m sensor grid

An illustration of target tracking using sensor grid of 40 m is shown in Fig. 5. The same target trajectories are used compared to the previous examples with the difference being a larger sensor grid. The SNR reference point, however, is different since it is defined as the signal-to-noise power ratio at the sensor if the target is placed at $\sqrt{2}D$ distance (D is the sensor grid distance, i.e., *10* or *40* meters in the examples shown above). It needs to be noted that a greater sensor grid distance causes less frequent active sensor group changes but requires more target power to ensure that the minimum *SNR* is at least *0 dB*.

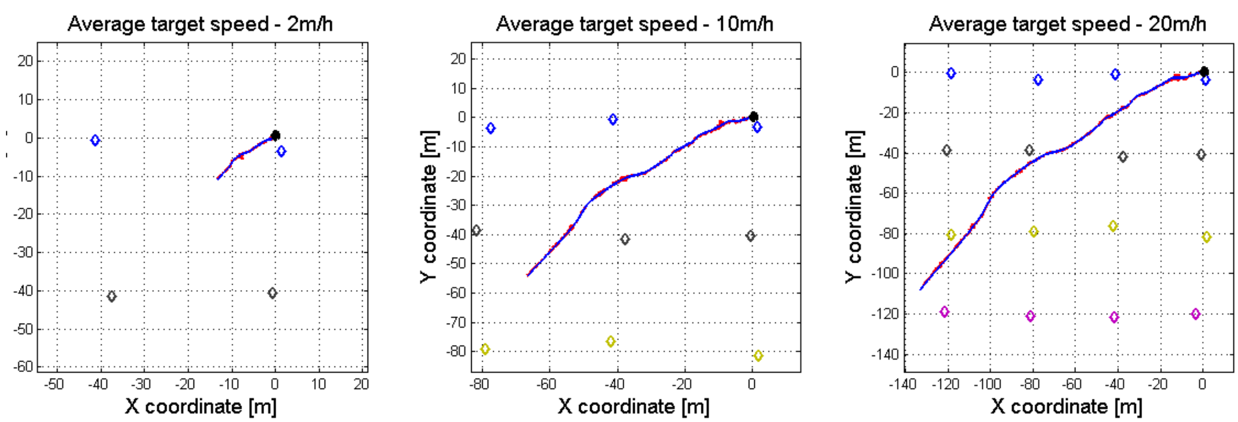

Figure 5. Target tracking - 40m sensor grid

A summary of the tracking results is shown in Fig. 6 (the metric that defines the performance is the position MSE for the whole track). Two observations can be made from the results:

1. Target tracking quality deteriorates gradually as the *SNR* decreases.
2. Target tracking quality deteriorates as target average speed increases. This increase can be attributed to more frequent active sensor group changes, which requires transformation of the Kalman filter state.

As indicated above the Kalman filter state is comprised of three log ratios and their corresponding derivatives. Since the origins of the four axes are the positions of the four active sensors, changing the active sensor set requires changing the axes and the corresponding Kalman filter state. Transforming the Kalman filter state to the new sensor set also requires that the system noise error covariance is transformed accordingly. The Kalman filter state transition is done by converting to a Cartesian space using old sensor set state and then computing the new filter state using the new sensor set. The system noise error covariance transformation is done by constructing a set of points with a distribution given by the old covariance, converting them to a Cartesian space, followed by estimating of the new error covariance using the new sensor set.

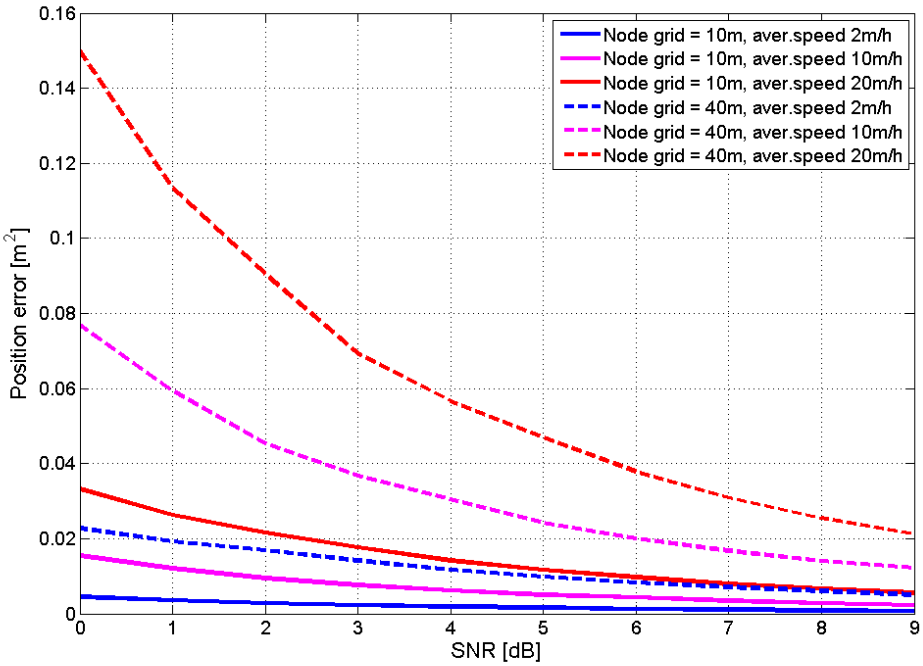

Figure 6. Target tracking error

5. CONCLUSIONS AND FUTURE WORK

Power tracking with omni-directional sensors has value from both a practical and an economical point of view due to its simple design, relaxed synchronization requirements, and low power consumption. In this paper we have presented a method that uses log power ratios to remove direct target position dependency on the target power. It is demonstrated that under certain assumptions, if the original observations are obtained in additive Gaussian noise, the log-ratio observations also are Gaussian. A new coordinate system/mapping was proposed and it was shown that a typical linear dynamic model in Cartesian coordinates can be propagated as an equivalent dynamic model in the log-ratio space. The proposed technique makes it possible to construct linear Gaussian system and observation models and allows for optimal tracking with a traditional Kalman filter framework. The results presented demonstrate that the proposed technique performs consistently over different noise levels, target speeds, and sensor grid densities, and presents a viable solution for low-cost, power efficient target tracking. The next step in exploring the topic would be to analyze whether any information regarding target position was lost due to undergoing the proposed non-invertible log-ratio transformation. Another interesting area to be investigated is, aside from its consistency, how the proposed technique performs when compared to an asymptotically optimal tracker such as the particle filter.

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