Wildlife Radio-Telemetry with Malfunctioning/ Mobile Receivers using Non-linear Approximation Filtering

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Abstract

Although GPS tracking systems can be used to obtain precise location information, it requires a substantial financial investment. In addition, malfunctions and battery failures of GPS tracking system have been reported [1]. In comparison, VHF radio telemetry is still a popular choice among scientists due to the low equipment cost and ease of maintenance.

Practicality of basic triangulating techniques is limited by the spatial dynamics of the animal. A slow moving animal can easily be tracked using a single antenna. Telemetry data from multiple antennas can significantly improve the accuracy of location. Often data from multiple antennas may create unintentional complication that can result in errors. Many algorithms have been formulated with the assumption that data is collected at specific, regular interval and is synchronized. Wildlife telemetry, in most cases, involves collecting data under less than perfect weather/terrain condition. It is common that some antennas may malfunction for brief periods, may not receive a signal during the data collection process or may fail due to breakdowns. Often obstructions can prevent some antennas from receiving a signal. It is also possible that the data collected by antennas may not be at synchronized time intervals. We investigate ways to use non-linear approximation filtering techniques to accommodate data gathered by at asynchronized time intervals, use of mobile antennas, and antenna failures during data gathering.

Introduction

The Kalman filter is the optimal solution to the Bayesian estimation problem for a given linear, stochastic, state-space system with additive Gaussian noise. Closed form solution have been derived for the aforementioned problem and have been extremely popular in the past [2], [3]. However, if the actual dynamical system drifts from a linear dynamical system or assumptions on characteristics of noise are incorrect, the filter tends to diverge. A variety of algorithmic modifications were invented in an attempt to compensate for the model errors that caused the misbehavior of the filter. This issue had been addressed to some extent by *Extended Kalman Filter* where an approximated linear system is derived for every calculation step [13]. The practicality of this approach has limited application to large complicated dynamical systems. Other techniques such as Uncented Kalman filter, Gaussian sum filter also suffer from the similar shortcomings as they either directly or indirectly use Kalman estimation techniques.

In recent years, computational power has reached to an extraordinary peak that one can implement algorithms once discarded due to their extensive computational cost. One type of powerful algorithm that resurfaced in recent years is the particle filter (PF) algorithm (Sequential Monte-Carlo algorithms) [6]. Recently particle based sampling filters have been proposed and used successfully to recursively update the posterior distribution of $p\left(x_k / \{y_1 \dots y_k\}\right)$ using *sequential importance sampling and resampling*. In contrast to Kalman filters particle filters in general can be used with non-linear, non-Gaussian dynamical systems. However, it needs to use a large amount of samples (particles) for a robust operation and accurate estimation which in many cases can be computationally expensive.

In order to trace the location of an animal, we need to estimate the current state x_k of an animal by processing the observations $\{y_1 \dots y_k\}$ available up to $t = k$.
This class of problems is tends to be more difficult and computationally more expensive. The beauty of particle filters is that it provides a solution to the localization problem and it exhibits excellent results.

Particle filters inherently computationally expensive which can limit the scope applications. To improve accuracy, modification to the algorithm as well as implementation has been introduced to dramatically reduce computational time. Algorithm has also been updated to account for malfunctions, data loses, and to handle asynchronous data. It is shown in this paper that convergence of the solution well within limits and accommodates various realistic field issues and conditions.

Particle Filtering

Consider the following discrete time non-linear system

$$x_{k+1} = f(x_k) + \omega_k$$

$$y_k = g(x_k) + \theta_k$$

where $x_k \in R^n, y_k \in R^d$ and ω_k, θ_k are independent noise processes of appropriate dimensions. It is assumed that the initial distribution x_0 is independent of ω_k and θ_k. Mean and variance of ω_k, θ_k are assumed to be known. Here we consider the Markovian state space models where state of the system x_k depend only on the previous state x_{k-1} in a probabilistic sense.

It is assumed that the probability distribution of x_0 is $p(x_0)$ and the distribution for the transition is $p(x_k \mid x_{k-1})$. It is also assumed that the conditional distribution of the outputs is $p(y_k \mid x_k)$.

The particle filter is to estimate the distribution $p(x_k | Y_k)$ using posterior probability distribution $p(Y_k | X_k)$ with $X_k = \{x_0, x_1, \ldots, x_k\}$ and $Y_k = \{y_1, y_2, \ldots, y_k\}$. Then it allows us to calculate any optimal estimate of the state, such as the conditional mean

$$\hat{x} = E[x_k | Y_k] = \int x_k p(x_k | Y_k) dx_k$$

Bayes' rule can be used to rearrange the posterior distribution,

$$p(X_k | Y_k) = \frac{p(Y_k | X_k) p(X_k)}{\int p(Y_k | X_k) p(X_k) dX_k}$$

A recursive formula for the aforementioned can be obtained as follows [6]:

$$p(X_{k+1} | Y_{k+1}) = p(X_k | Y_k) \frac{p(y_{k+1} | x_{k+1}) p(x_{k+1} | x_k)}{p(y_{k+1} | Y_k)}$$ Marginal distribution of $p(x_k | Y_k)$ can be calculated as follows:

$$p(x_k | Y_k) = \frac{p(y_k | x_k) p(x_k | Y_{k-1})}{\int p(y_k | x_k) p(x_k | Y_{k-1}) dx_x}$$

Particle filter (PF) is an approximation that uses sequential Monte Carlo methods to reach a solution with a finite number of calculations.

When the initial state is unknown, and needs to be found, the initial distribution is approximated by a uniform distribution over an appropriate region of the state space. Following steps describe the algorithm in detail.

Algorithm Particle Filtering

Step 1

- Draw N samples x_0 from the state space with importance weights=1/N and set t = 1

Step 2

- Draw N samples $\tilde{x}_t^{(i)}$ from $p\left(x_t | x_{t-1}^{(i)}\right)$ $i = 1, \ldots, N$
- Evaluate the importance weights $w_k^{(i)} = p\left(y_k | \tilde{x}_k^{(i)}\right)$
- Normalize the weights

Step 3

- Resample with replacement N particles from $\tilde{x}_t^{(i)}$ according to the weights
- Set $t \rightarrow t+1$ and go to step 2

Conditional probability of each particle ($\tilde{x}_t^{(i)}$) at $t=k$ is changed at step 2. Resampling in step 3 is based on the weights associated with the particles that could result in small, average and large values according to the conditional probability. Resampling draws N samples from $\tilde{x}_t^{(i)}$ $i = 1,\ldots, N$ by repeating the particles with larger weight and removing the ones with smaller weights. Even though this step improves the resolution of the area with higher probability, it does not improve the accuracy of the initial state x_0 .

Receivers/Animal Behavior

Consider an animal in an environment without visible signs of location to the naked eye. The trajectory of such an animal follows an irregular and random path. Such path depends on many factors including seasonal changes, competition for food, predators, health, age etc. While some animals travel in herds (fish, geese, deer etc) others may avoid animals of same type except for mating seasons.

The movement of an animal is regarded to be the result of two components.

1. Influence due to the heard behavior, seasonal migration patterns or movement on restricted geographic area.
2. Random movements caused by evasive actions from predators, competing animal behavior and roaming for food.

Animal movement u is governed by the following equation.

$$\frac{du}{dt} = -\varsigma u + A(t) \qquad (1)$$

If u represents the movement of the animal then the first component is calculated to be $-\varsigma u$ where ς is coefficient determined based known herd/migratory behavior. Component $A(t)$ represents the random movement the animal (ex: evasive maneuvers). The following assumptions are crucial for the solution of (1).

1) The mean of the fluctuating behavior $A(t)$ over animals with the same initial location u_0 at $t = 0$ is zero. i.e. $E\{A(t)\} = 0$
2) It is assumed that $A(t)$ is independent of u . The values $A(t)$ at two different times t_1 and t_2 are not correlated except for small intervals $(t_1 - t_2)$

$$E\{A(t_1)A(t_2)\} = \phi(| t_1 - T_2 |)$$

where $\phi(x)$ is a function with a very sharp maximum at $x = 0$, $\phi(x)$ being very small for $x \neq 0$

3) The correlation of $A(t)$ obey the following:

$$E\left\{A(t_1)A(t_2)\ldots A(t_{2n+1})\right\}=0$$
$$E\left\{A(t_1)A(t_2)\ldots A(t_{2n})\right\}=$$
$$\sum_{all\ pairs} E\left\{A(t_i)A(t_j)\right\}E\left\{A(t_k)A(t_l)\right\}\ldots$$

Assumption (2) describes the sampling interval of time Δt during which, rapid changes to $A(t)$ is expected where as changes in $u(t)$ is expected to be very small. To solve the above equation, we must solve a stochastic differential equation. That is the probability of the solution $W(u,t;u_0)$ is u at the time t, given $u-u_0$ at $t=0$.

Using the knowledge of linear first order differential equations we can solve equation (1)

$$u=u_0e^{-\varsigma t}+e^{-\varsigma t}\int e^{-\varsigma \tau}A(\tau)d\tau \cdot$$

Since an analytical solution involves rigorous calculations, a numerical solution is adopted in many situations.

Rewrite (1),

$$u_k-u_{k-1}=-\varsigma u_{k-1}\Delta t_k+\sigma A_k(\Delta t_k)$$

where $\Delta t_k=t_k-t_{k-1}$. Then

$$u_k=u_{k-1}(1-\varsigma\Delta t_k)+\sigma A_k(\Delta t_k)$$

and this can be solved iteratively.

Simulations & Results

One of the major drawbacks of existing wildlife radio telemetry techniques is the difficulty to adapt to unexpected changes in reception characteristics of antennas. Reception range of a transmitter depends on multitude of factors. Signal output power (depends on the size of battery capacity), terrain, vegetation, and orientation of the animal are some of the factors that affect the range of the transmitter. The method we introduced accommodates many field related issues that traditional techniques would require re-calculation. Simulations were carried out to illustrate the effectiveness of the initial sample size, noise levels at the receivers, malfunctioning receivers, and use of mobile receivers.

Slow moving animals can be tracked with higher precision using the standard triangulation techniques. In contrast, tracking an animal in a large area and/or with fast movements is either unable or highly challenging using existing techniques. Therefore, we have simulated a fast moving animal that may roam in a large area. Such an analysis will test and gauge the robustness and effectiveness of the algorithm. For simulation purposes we considered a rectangular area of 50 miles by 50 miles where the animal is expected to be located. The area of the possible presence of an animal is determined based on the last known location, animal behavior patterns, and the speed of its movement.

Simulations are performed for an animal with a random movement described by a normal distribution with 0.7 mile standard deviation. Three antennas were utilized for simulations purposes. Measurement error on each of the antenna is assumed to follow a normal distribution with 8 degrees of standard deviation. Standard deviation of a popular Yagi antenna can range from 1 degree to 24 degrees [11], [12]. Since the algorithm does not require static or identical characteristics of antennas, antennas can be switched, removed or performance criteria can be updated while data is being collected. Such changes can readily be incorporated in to the calculation process without giving rise to any complications.

Effect of sample size

Initial sample size (gird size) plays a major role in the accuracy of the solution. Not only a larger sample (smaller gird size) improves the accuracy but also increases the computational time.

Figure 1
Estimation error with initial sample size

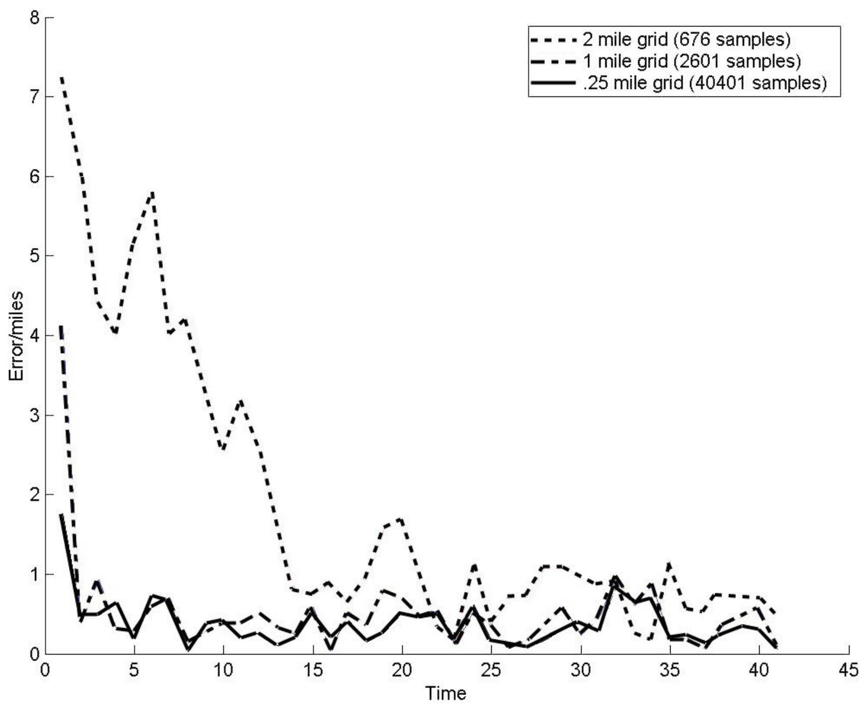
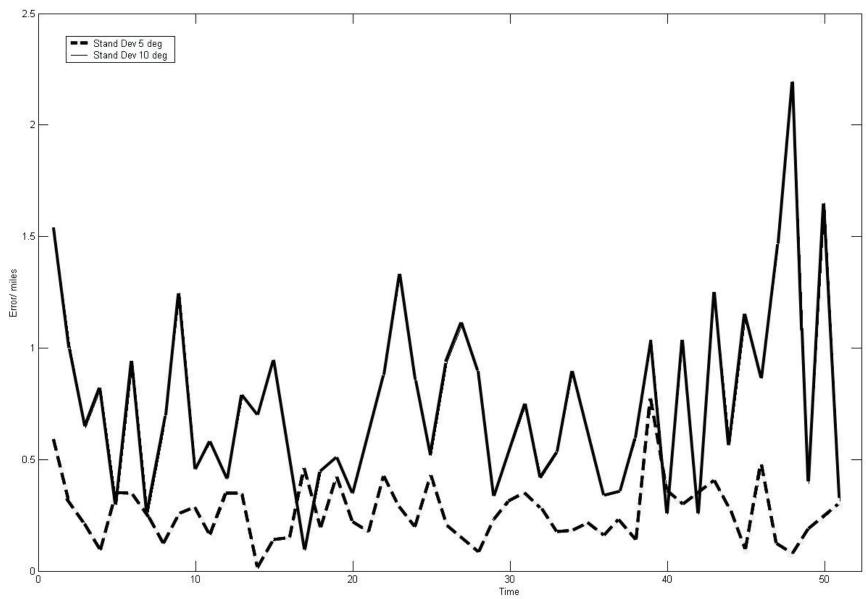


Figure 1 shows that a larger initial sample converge faster toward the location of the animal compared to a smaller initial sample. However, as the simulation results indicate, a very large sample size (40401 samples) which utilize substantial amount of computing power does not provide significant improvement over a 2601 sample size. Figure 1 indicates that a gird size (sample size) small enough to capture the movement characteristics of the animal provide a faster convergence with a better accuracy.

Effect of noise at the receiving antennas

Two trials of simulations were conducted to observe the performance of the particle filter algorithm under white noise with a standard deviation of 5 degrees and 10 degrees. Figure 2 shows the highly directional antennas lead to a better estimation of the location. However, figure 2 shows antennas with higher noise also provide a desirable estimate of the location.

Figure 2
Estimation error with noise at the receivers



Sensor failure/intermittent reception

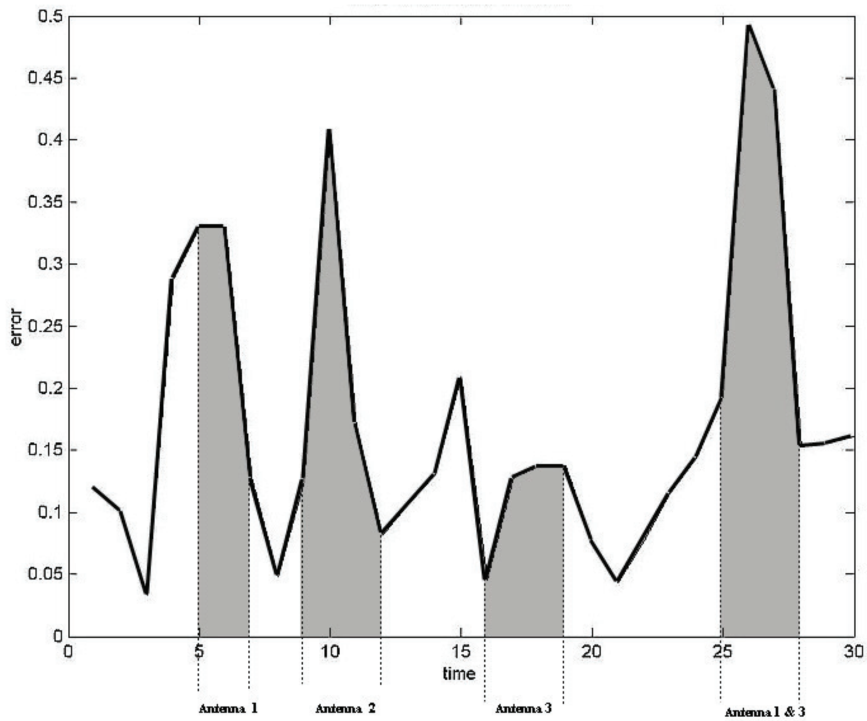
Often data is collected in areas with unfavorable conditions that can either damage equipments or disrupt signal reception. Importance weights calculation was modified to utilize the observations that are available at given time.

$$w_k^{(i)} = p\left(y_k^a \mid \tilde{x}_k^{(i)} \right)$$

where y_k^a is the k^{th} available observation (data received by k^{th} antenna). Thus estimation process can be continued without the need of a recalculation. Receivers failing at random intervals of time were simulated and the error in estimation was calculated. Figure 3 shows the error in estimation of animal location with multiple receivers failing in random intervals (highlighted).

It is evident from the figure 3 that the algorithm performs exceptionally well under these circumstances. This modification to the algorithm can also be used for data that has been collected at different time intervals by multiple antennas.

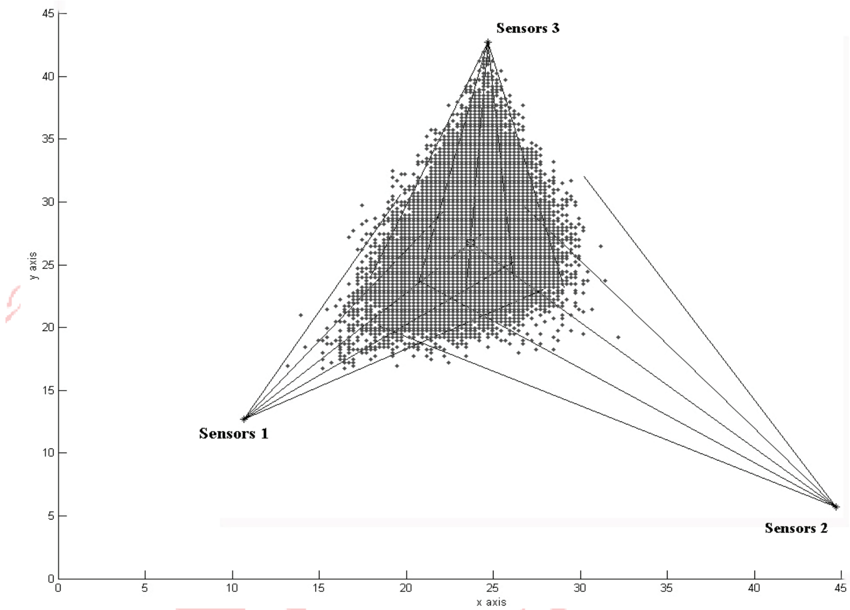
Figure 3
Estimation error with missing receiver data



Use of mobile receivers

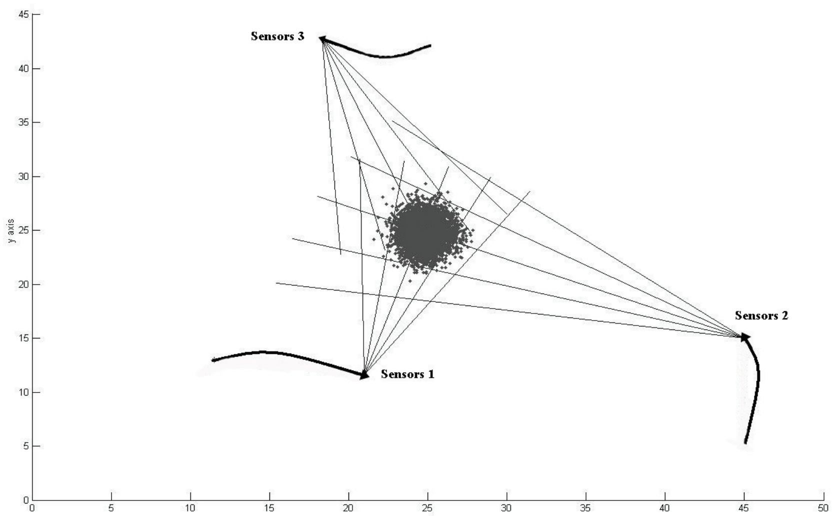
A set of mobile receivers have the advantage of relocating themselves to avoid bad reception and to narrow the search area. Since vehicle/handheld GPS systems are inexpensive and widely available, we assume that the exact location of a receiver is known. For simulation purposes, we chose smooth paths to represent roads that the vehicles followed. However, algorithm is independent of the smoothness/complexity of a route followed. Figure 4 shows the possible locations of the animal after the first re-sampling (iteration). Lines emanating from Receivers are to indicate directional uncertainty of each sensor (two adjacent lines represent one standard deviation).

Figure 4
Possible locations after the first iteration



Possible animal locations are spread over a large space and this area is significantly narrowed to a smaller region after the 10th iteration (figure 5).

Figure 5
Possible locations after the tenth iteration



Every iteration improves the estimate for the possible location of the animal. This information, current estimate of the location, can be used to navigate/guide each vehicle/person with an antenna for faster tracking.

Conclusions

Use of Particle filters in estimating the location of an animal is explored under Mobile receivers and failure of equipment. We can anticipate sequential Monte Carlo methods would result in better convergence for similar types of problems. This paper considers an altered form of a particle filter algorithm along with modifications to importance weights formula. The modification resulted in an algorithm that accommodates common field related issues. Simulation indicates that estimation process can be continued without an interruption under intermittent data gatherings.

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