

July 2012

MINIMAX FILTERING IN WIRELESS SENSOR AND ACTOR NETWORKS

K. RAMESH

Department of CSE, JNT University, Anantapur, India, rameshkarlagunta@gmail.com

S. Vasundra

Department of CSE, JNT University, Anantapur, India, vasundaras@rediffmail.com

Follow this and additional works at: <https://www.interscience.in/ijssan>



Part of the [Digital Communications and Networking Commons](#), and the [Electrical and Computer Engineering Commons](#)

Recommended Citation

RAMESH, K. and Vasundra, S. (2012) "MINIMAX FILTERING IN WIRELESS SENSOR AND ACTOR NETWORKS," *International Journal of Smart Sensor and Adhoc Network*: Vol. 2 : Iss. 4 , Article 10.

DOI: 10.47893/IJSSAN.2013.1178

Available at: <https://www.interscience.in/ijssan/vol2/iss4/10>

This Article is brought to you for free and open access by the Interscience Journals at Interscience Research Network. It has been accepted for inclusion in International Journal of Smart Sensor and Adhoc Network by an authorized editor of Interscience Research Network. For more information, please contact sritampatnaik@gmail.com.

MINIMAX FILTERING IN WIRELESS SENSOR AND ACTOR NETWORKS

K.RAMESH¹ & S.VASUNDRA²

^{1,2}M.Tech, Department of CSE, JNT University, Anantapur, India
E-mail: rameshkarlagunta@gmail.com , vasundaras@rediffmail.com

Abstract- In this paper to handle the mobility of actors a hybrid strategy that includes location updating and location prediction is used. The usage of Kalman Filtering in location prediction high power and energy consumptions. To avoid the drawbacks of Kalman Filtering in location prediction, we make use of Minimax filtering (also Known as H^∞ filtering). Minimax Filter has been used in WSNs by minimizing the estimation error and maximizing the worst case adversary noise. Minimax filtering will also minimize power and energy consumptions.

Keywords- *Wireless Sensor and actor networks,, minimax filtering, mobility, power efficient.*

I. INTRODUCTION

Wireless Sensor and Actor networks (WSNs) are distributed wireless networks of heterogeneous devices referred to as sensors and actors. In Wireless Sensor and Actor Networks (WSNs) the collaborative operation of sensors enables the distributed sensing of physical phenomenon, while actors collect and process sensor data and perform appropriate actions. Sensors are low-cost, low-power, multi functional devices that communicate in short distances. Actors are resource-rich devices equipped with high processing capabilities, high transmission power and long battery life. Actors collect the sensor data and process that data and consequently perform actions in the network.

WSNs are used in several applications. In some applications, actors are part of the network and perform actions based on the information gathered by sensors. For example, In Distributed Robotics the task is not completed by a single robot but a team of collaborating robotics. Information about the surrounding environment is usually gathered by onboard sensors and team members exchange sensor information to move or perform actions.

In WSNs, the sensors distribute the sensed data after detecting an event that is occurred in the environment. The event data are distributively processed and transmitted to the actors, which gather, process, and eventually reconstruct the event data. When an event occurred in the environment the data flows between sensors and actors, this process is referred to as sensor-actor coordination. Once an event has been detected, actors coordinate to reconstruct it, to estimate the event characteristics and make a collaborative decision on how to perform the action. This process is referred to as actor-actor coordination.

Sensors and actors are movable devices in WSNs. In previous work on WSNs [1], uses location

management scheme for location updates and location prediction. It uses Voronoi diagrams for location updation and Kalman Filtering for location prediction. Kalman Filtering used in WSNs will cause some problems. The main drawbacks of Kalman Filtering are it fails to identify the unknown noise and fails to minimize the estimation error. By replacing Kalman Filtering with Minimax Filtering we can minimize the estimation error and it can identify the worst case adversary unknown noise.

II. RELATED WORK

Wireless Sensor and Actor Networks (WSNs) research challenges and several application scenarios are described along with challenges for effective sensor-actor coordination and actor-actor coordination in [7]. As discussed in [2] There are many challenges in Wireless Sensor and Actor Networks, especially due to resource constraints. In [5], [8] the authors considered the issue of real-time communication in sensor networks. The SPEED protocol [5] provides real-time communication services and is designed to be a stateless, localized algorithm with low control overhead. MMSPEED [8] is an extension of SPEED that can differentiate between flows with different delay and reliability requirements. SPEED and MMSPEED try to provide real-time delivery of individual flows from different sensors. None of these papers deals with sensor-actor coordination or with actor-actor coordination.

Some research papers like [9] deals with the problem of mutual exclusion in WSNs. In [6], the authors deal with the problem of “hazards” which consists of out-of-order execution of queries and commands due to the lack of coordination between sensors and actors. To enable a wide range of trade-offs between delay and energy consumption that controls the wake-up cycle of sensors based on the experienced packet delay [13] presents a delay-energy aware routing

protocol (DEAP) for sensor and actor networks. However, the paper only deals with sensor-actor communication.

The mobility of WSANs has been handled in [1] with sensor-actor coordination and actor-actor coordination using power-controlled energy-delay adjustment and event preemption for multi actor task allocations respectively. It also provides a solution for multi actor task allocation problem by selecting the best actor team that minimizes energy consumption. However it uses Kalman filtering in location prediction, which is having two major limitations. First, Kalman Filtering assumes that the noise properties are known, if the system have unknown noise then it fails to identify that. Second, Kalman Filtering minimizes average estimation error and fails to minimize worst case estimation error.

The above limitations gave raise to Minimax Filtering also known as H_∞ filtering. The usage of Minimax Filtering in Wireless Sensor Networks has been discussed in [3]. The Minimax filter is a robust filter that minimizes the estimation error by considering the worst case noise.

III. LOCATION MANAGEMENT

The network is composed of N_S sensors and N_A actors, with $N_S \gg N_A$. Each sensor is equipped with a low data rate radio interface. Actors are equipped with two radio transmitter i.e., a low data rate transmitter to communicate with the sensors and a high data rate wireless interface for actor-actor communication so that each sensor will route information to its closest actor, unless an alternative actor is preferable in case of congestion.

In general location management may follow two strategies: *location updating* and *location prediction*. Location updating is a passive strategy in which each actor periodically broadcasts its position to the neighboring sensors. Location prediction is a dynamic strategy in which sensors proactively estimate the location of their neighboring actors. *In this case we used Minimax Filtering for predicting the positions of the actors* for location updates we proposed location management scheme based on spatial and temporal domains. In spatial domain update messages sent by mobile actors to sensors. Therefore, sensor-actor communications are localized. Hence in the spatial domain, broadcasts can be limited to Voronoi diagrams [11]. In the temporal domain, location updates can be limited to actor positions that cannot be predicted at the sensor side. Location updates are triggered at the actors when the actual position of the actor is far away from the predicated sensor based on past measurements. Therefore, actors that moves following predictable paths.

A. Voronoi diagrams in location updation

We use Voronoi diagrams in location updates. The Voronoi diagram of a set of discrete sites partitions the plane into a set of convex polygons such that all points inside a polygon are closed to only one site. For their properties and ease of computation, Voronoi diagrams are previously used in the area of sensor networks. In [12], Voronoi diagrams are used to measure how well an object is moving on an arbitrary path can be observed by the sensor network over a period of time. In [13], an optimal polynomial-time worst- and average-case algorithm for coverage calculation with homogeneous isotropic sensors is derived.

The Voronoi cell of an actor a_i contains all points of the plane that are closer to a_i than to any other actor in the network. A sensor s is said to be *dominated* by an actor a_i if its location lies in the Voronoi cell of a_i . Every actor is responsible for location updates to sensors in its Voronoi cell. Each sensor will thus expect to receive location updates from the actor which is dominated by that sensor.

The energy consumption for location updates will drastically reduced with respect to flooding. With a flooding like protocol each actor sends a message to its N neighboring sensors. We consider the link metric $E = 2E_{elec} + E_{amp}d^\alpha$, where α is the path loss propagation exponent ($2 \leq \alpha \leq 5$), E_{amp} is a constant [$J/(bits.m^\alpha)$], and E_{elec} is the energy needed by the transceiver circuitry to transmit or receive one bit [$J/bits$]. Each sensor, upon receiving the message, forwards it by broadcasting again. On this first hop only, the energy consumption is $N_A \cdot (NE_{elec} + N(E_{elec} + E_{amp}d^\alpha + NE_{elec})) = N_A \cdot (2N E_{elec} + NE_{amp}d^\alpha + N^2 E_{elec})$. At least we need a message from each actor to reach each sensor in the network, and the same message can potentially be relayed to each other node in the network before it is discarded. This is clearly a worst-case scenario, but it provides an indication of the scaling law for the energy consumption. Instead, provided that each actor can transmit data within its Voronoi cell, no forwarding is needed, and hence, the energy consumption is in the order of the number of sensors (energy needed to receive the update packets). Hence, the worst-case energy consumption of a flooding scheme increases as a function order of $O(N_S^2 \cdot N_A)$, and most of the energy burden is on the sensors. Conversely, if the actor is able to reach all sensors in its Voronoi cell in one hop, which may be true in many practical cases, the energy consumption increases as a function order of $O(N_S)$, and most of the energy burden is on the actors.

B. Minimax Filtering in location prediction

Location updates can be triggered at the actors only when the actual position of the actor is "far" from what can be predicted at the sensors based on past measurements. Therefore, actors that move

following predictable paths will need to update their position much less frequently than actors that follow temporally uncorrelated paths. In [4], the Kalman filtering is used for adaptively varying frequency of location updates based on sensor side previously received updates.

We further observe that Kalman filtering is used as a means of decentralized estimation of objects in sensor networks in [14], [15] and in wireless multimedia sensor networks in [16] where as in [4], Kalman filtering is used for object tracking with the design of a location management to enable geographic routing in WSANs. In [3], Minimax filtering is used to target tracking in sensor networks. In this paper we introduced Minimax filtering in WSANs, instead of Kalman filtering for location prediction.

Minimax filtering is used to estimate the states of a dynamic system based on the measurements related to the estimated states, the measurement model and the system model. It looks the same as other state estimators, such as Kalman filtering. However, the difference is that the system state model includes fictitious adversary disturbances, which includes some partially unknown noise. Minimax filtering is a robust filter that minimizes the estimation error by considering the worst case noise. Here actors are assumed to be endowed with an onboard localization system (e.g., GPS), while sensors predict the position of actors based on Minimax filtering of sparse measurements (taken at the actor and transmitted to the sensors).

The dynamic movement model for the i^{th} actor in two-dimensional coordinates can be described by continuous-time linear dynamic system. In WSANs multiple sensors and multiple actors are presented. The sensor nodes have to estimate the position of actor nodes. From [18] the actor position can be estimated with the discrete-time dynamic equation.

$$x_i^{t+1} = A x_i^t + B w_i^t + d_i^t. \quad (1)$$

Equation (1) represents the state transition equation for the system describing the motion of actor i between t and $t+1$, where $x_i^t = [x_i^t, y_i^t, x_i^t, y_i^t]^T$ represents position and velocity of actor i at step t ; $w_i^t = [w_i^{t,x}, w_i^{t,y}]^T$ represents the system noise in the control input; $d_i^t = [d_i^{t,x}, d_i^{t,y}]^T$ represents the adversary disturbance. A, B are the matrices of the appropriate dimensions with bounded entities. Assume that the target actor is intelligent and can maximize the estimation error. Let \hat{x}_t denotes the estimated state, the estimation error is $x_t - \hat{x}_t$. The adversary disturbance is modeled as

$$d_t = L(C(x_t - \hat{x}_t) + n_t). \quad (2)$$

Where L is gain to be determined, n_t is Gaussian noise with zero mean diagonal covariance matrix $S > 0$. C is the position observed by the actor at step t is related to the state by the *measurement equation*

$$y_i^t = C_i x_i^t + v_i^t. \quad (3)$$

where $y_i^t = [y_i^{t,x}, y_i^{t,y}]$ represents the *observed position* of the actor at step t , $v_i^t = [v_i^{t,x}, v_i^{t,y}]$ represents the *Gaussian noise* with zero mean and covariance matrix $R \geq 0$. Thus, the observed position of the actor y_i^t is, the actual position of the actor affected by a Gaussian noise.

The Minimax filter provides computationally efficient set of recursive equations to estimate the state of such process. The joint use of Minimax filter at the sensor and actor sides enables reducing the number of necessary location updates. In fact, the filter is used to *estimate the position* at the actor based on measurements, which is a common practice in robotics, and to *predict* the position of the actors at the sensors, thus reducing the message exchange. The position of actor i can be estimated and predicted at the sensors in its Voronoi cell, based on the measurements y_i^t taken at the actor and broadcast by the actor. At step t , each sensor s in i 's Voronoi cell updates the state (that represents position and velocity of the actor) based on the equations

$$\hat{x}_{i,s}^{t+1} = A \hat{x}_{i,s}^t + K(y_i^t - C \hat{x}_{i,s}^t) \quad (4)$$

Where K is the gain of the Minimax filter, the estimation error is defined by

$$e_i^t = x_i^t - \hat{x}_i^t \quad (5)$$

The Minimax algorithm can be summarized as:

$$\sum_t^{-1} = P_{i,s}^t + C' (R^{-1} - S^{-1}) C \quad (6)$$

$$P_{i,s}^{t+1} = A \sum_t A' + BQB' \quad (7)$$

$$K_{i,s}^t = A \sum_t C' R' \quad (8)$$

The sensor s predicts the state of actor i before receiving the measurement (a priori estimate) with (4). After receiving the measurement the from the actor y_i^t , sensor s updates the Minimax filter gain $K_{i,s}^t$ and corrects the state estimate and covariance matrix according to the measurement, using (6), (7) and (8). In particular (7) updates the covariance matrix, (8) updates the Minimax gain and (4) calculates the new state.

IV. SIMULATION RESULTS

A. Simulation Specifications:

OS	: Fedora 9
Simulator	: NS2
Topology	: Wireless Topology
Number of Nodes	: 49
Maximum Transmission range	: 40 m
Simulation time	: 400s
Area of the network	: 100X100 m

B. Simulation Results:

Network Simulator (NS2) is used for simulating the existing and proposed systems. NS2 is an IEEE standardized simulator for simulating Networks.

In Fig.1, we show a comparison of the average power consumption in WSNs using Kalman Filtering and Minimax Filtering with increasing forwarding range. The power consumption in WSNs using Kalman Filtering is drawn with green line and the power consumption in WSNs using Minimax Filtering is drawn using red line. In all the cases the power consumed by Kalman Filtering is more than that of the power consumed by Minimax Filtering.

In Fig.2, we show a comparison of energy consumption in WSNs using Kalman Filtering and Minimax Filtering. The energy consumption for Kalman Filtering is more than the energy consumption for Minimax Filtering.

V. CONCLUSIONS

We discussed the drawbacks of Kalman Filtering in location prediction process of a WSN. The drawbacks of Kalman Filtering are over come by Minimax Filtering. Using Minimax Filtering the estimation error was minimized by maximizing the worst case noise. By replacing Minimax Filtering with Kalman Filtering in location prediction of WSNs reduce the power and energy consumptions.

REFERENCES

- [1] Tommaso Melodia, Dario Pompili, and Ian F.Akyildiz "Handling Mobility in Wireless Sensor and Actor Networks", *IEEE Trans, Mobile Computing*, vol. 9, no.2, Feb.2010.
- [2] J.A.Stankovic, T.F. Abdelzaher, C.Lu, L.Sha, and J.Hou, "Real-Time Communication and Coordination in Embedded Sensor Networks," *Proc.IEEE*, Vol.91, no.7, pp.1002-1022, July 2003.
- [3] Dongbing GU "A Gametheory approach to Target tracing in sensor networks," *IEEE Trans, Systems, MAN and Cybernetics-part B: Cybernetics*, Vol.41, no1, Feb.2011.
- [4] T. Melodia, D. Pompili, and I.F. Akyildiz "A Communication architecture for mobile Wireless Sensor and Actor Networks" *Proc. IEEE Conf., Sensor, Mesh and Ad Hoc Comm.and Networks (SECON)*, Sept.2006.
- [5] T.He, J.Stankovic,C.LU, and T.Abdelzaher "SPEED: A Real-Time routing protocol for Sensor Networks," *Proc. IEEE int'l Conf. Distributed Computing Systems(ICDCS)*,pp. 46-55,May 2003.
- [6] R.Vedanham, Z.Zhuang, and R.Sivakumar, "Hazard Avoidance in Wireless Sensor and Actor Networks",*Computer Comm.*,vol. 29,nos. 13/14,pp.2578-2598,Aug.2006.
- [7] J.I.F.Akyildiz and I.H.Kasimoglu, "Wireless Sensor and Actor Networks: Research Challenges,"*Ad Hoc Networks*, vol. 2, no.4, pp.351-367, Oct. 2004.
- [8] E.Felemban, C.-g. Lee, E.Ekici, R.Boder, and S. Vural, "Probabilistic QoS Guarantee in reliability and Timeliness Domains in Wireless Sensor Networks," *Proc. IEEE INFOCOM*,Mar. 2005.
- [9] R.Vedanham, Z.Zhuang, and R.Sivakumar, "Mutual Exclusion in Wireless Sensor and Actor Networks," *Proc. IEEE.Conf.Sensor, Mesh and Ad Hoc Comm. And Networks (SECON)*, Sept. 2006.
- [10] A.Durresi, V.Paruchuri, and L.Barolli, "Delay-Energy Aware Routing Protocol for Sensor and Actor Networks",*Proc. Int'l. Conf. Parallel and Distributed Systems*, vol.1, pp.292-298, July 2005.
- [11] F.Aurenhammer, "Voronoi Diagrams- A Survey of a Fundamental Geometric Data Structure," *ACM Computing Surveys*, vol.23, pp.345-405, 1991.
- [12] S.Meguerdichian, F.Koushanfar,G.Qu, and M.Potkonjak, "Exposure in Wireless Ad-Hoc Sensor Networks," *Proc. ACM MobiCom*,pp.139-150,2001.
- [13] S.Megerian, F. Koushanfar, M.Potkonjak, and M.Srivastava, "Worst and Best-Case Coverage in Sensor Networks",*IEEE Trans. Mobile Computing*, vol.4, no.1,pp.84-92,Jan./Feb.2005.
- [14] R.Olfati-Sabar, "Distributed Tracking for Mobile Sensor Networks With Information-Driven Mobility," *Proc. AM. Control Conf.*, July 2007.
- [15] A.Ahmed, M. Gani, and F.Yang "Decentralized Robust Kalman Filtering for Uncertain Stochastic Systems over Heterogeneous Sensor Networks," *Signal Processing*, vol. 88, no.8, pp.1919-1928, 2008.
- [16] H.Medeiros, J. Park, and A.Kak, "Distributed Object Tracking using a Cluster-Based Kalman Filter in Wireless Camera Networks," *IEEE J. Selected Topics in Signal Processing*, vol.2, no.4, pp.448-463, Aug.2008.
- [17] L.Hu and D.Evans, "Localization for Mobile Sensor Networks," *Proc. ACM MobiCom*,Sept.2004.
- [18] Dongbing Gu and Huosheng Hu "Distributed Minimax Filtering for Tracking and Flocking", *IEEE int'l Conf. on Intelligent Robotics and Systems*.pp.18-22.Oct 2010.

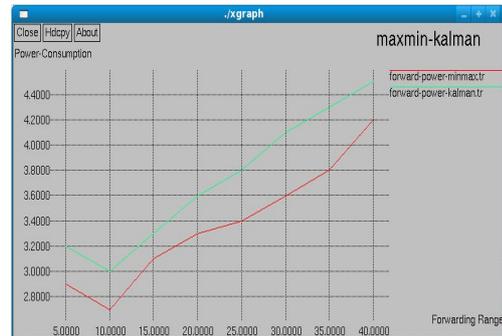


Fig.1. Average power consumption versus forwarding range in WSNs using Kalman filtering and Minimax Filtering.

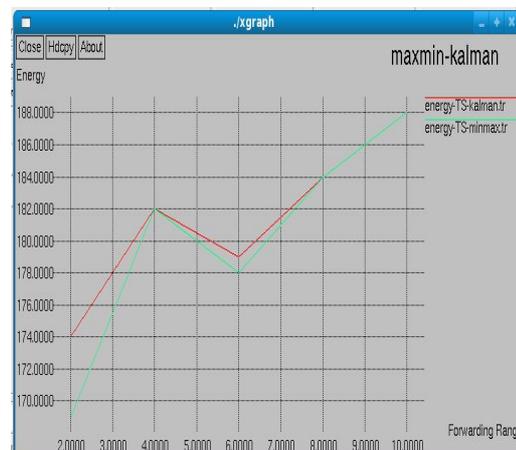


Fig.2. Energy consumption in WSNs using Kalman filtering and Minimax Filtering

