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Research Article

Energy-Efficient Constant Gain Kalman Filter Based Tracking in Wireless Sensor Network

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Target tracking is one of the most widely used applications of wireless sensor network (WSN). Efficient usage of energy is a key issue in WSN application such as target tracking. Another important criterion is a tracking accuracy that can be achieved by using appropriate tracking mechanism. Because of the special characteristic of WSN, there is a trade-off between tracking accuracy and power consumption. Our aim is to improve tracking accuracy as well as provide energy-efficient solution by integrating the concept of clustering and prediction techniques. This paper presents Energy-Efficient Constant Gain Kalman Filter based Tracking (EECGKFT) algorithm to optimize the energy usage and to increase the tracking accuracy. There is also a need to collect data from network having a mobile Base Station (BS). Hence, performance of proposed algorithm is analyzed for a static BS and also for mobile BS. The results depict that proposed algorithm performs better compared to the existing algorithms in energy efficiency and prediction accuracy. Analysis of results validates that EECGKFT increases energy efficiency by reducing transmission of unnecessary data in the sensor network environment and also provides good tracking results.

1. Introduction

Wireless Sensor Network (WSN) has been extended in various different applications from commercial to industrial and military to medical domains. With thousands of sensor nodes WSN has been deployed to observe the physical environment and to detect the event of interest. In general, tracking includes monitoring and detecting the target location.

One of the basic issues of WSN is the energy constraint. Maximum energy consumed during data communication from sensor nodes to the BS rather than data processing [1]. Network lifetime depends on the energy required for the activity of the sensor nodes. Once sensor nodes are placed, it is not possible to charge or replace its battery. To extend the lifetime of the network, it is necessary that the energy of the sensors is used efficiently.

This paper presents a hybrid Energy-Efficient Constant Gain Kalman Filter based Tracking (EECGKFT) algorithm to detect and track the moving target in sensor network area. The proposed algorithm relies on clustering and prediction based collaborative approach. The proposed technique provides energy-efficient solution by reducing redundant data transmission among sensor nodes and the BS. The proposed algorithm is analyzed for static BS model when BS location is at fixed position and also for mobile BS model when BS moves dynamically in sensor network area. It finds accurate target path and reduces localization error.

The next section describes an overview of related work in this area. Section 3 describes the proposed EECGKFT algorithm and its pseudocode. Section 4 carries simulation results and analysis. Finally, the paper is concluded in Section 5.

2. Related Work

Target tracking algorithms are categorized as tree based, cluster based, prediction based, and hybrid based algorithms [2, 3]. Hierarchical tree is represented in tree based architecture while cluster based network divides network into cluster that collaboratively collect and process the data [4]. Prediction based algorithms predict the next location of the moving target based on historical data available. Hybrid

algorithms combine the features of different network architectures. Several existing algorithms are discussed below in brief.

In [5], a cluster based approach to track the moving target is discussed. This algorithm reduces the number of nodes taking part in tracking process and also reduces the duplicate data being sent to the BS. This approach provides energy-efficient solution by decreasing number of nodes participated in detecting the target but it is limited to static cluster formation.

The cluster and prediction based approach is proposed in [6–9]. In [6], the proposed algorithm reduces data transmission between sensor nodes. Only selected sensor nodes can calculate location of target and one of the nodes can transmit data to the cluster head (CH). The algorithm proposed in [7] provides recovery mechanism when target is not found within predefined region but it requires extra energy to recover the lost target. In [8], authors use distance and energy parameters to select the node for tracking. Nodes with lower energy do not participate in the communication and remain in the network for a longer time which in turn increases the network lifetime. In [9], the authors proposed the mobility prediction method that predicts the movement of target based on available target's data. The curve fitting algorithm is used to model the target mobility pattern in this technique. These algorithms are limited to linear prediction methods to predict the next location of the target.

The boundary problem solutions are presented in [10–14] when target moves along the boundary region. In [10], the proposed algorithm forms dynamic clusters when target moves near to the static cluster's boundary area. However dynamic cluster formation and dismissing required more energy. To overcome this problem the authors proposed HCMTT in [11] that merges dynamic clusters when two targets move near to each other. Authors in [12] extended HCMTT and used incentive based mechanism for dismissal of dynamic cluster. In this approach, dynamic CH preserves a variable point that increases if target remains in its cluster for longer time and decreases the variable points if the target leaves the dynamic cluster. To solve the boundary problem author presented incremental clustering technique to track the moving object [13]. Gaussian Adaptive Resonance Theory (GART) based incremental clusters are formed in conjunction with static cluster and continue tracking in an energy-efficient way. In already visited path, this algorithm can keep some recent clusters to track the moving target. So the problem of dynamic cluster formation is solved using incremental clustering. These algorithms require higher energy consumption to solve boundary problem by forming extra clusters. In [14], the authors develop an efficient failure-prone object detection algorithm that detects and recovers from binary node failures. This scheme increases the boundary estimation accuracy.

In existing approach, the target localization is carried out by local sensor nodes. The trilateration approach is used to locate the target in [5–7, 13]. The target location is calculated using sensing range based method in [10–12]. The prediction kinematic used cannot estimate exact target location for noisy environment.

An Interactive Multiple Model (IMM) based tracking scheme for WSN has been proposed in [15]. This method uses multiple filters and multiple sensors to detect and track the targets. Hence the energy consumption is high for tracking. A distributed particle filter (PF) is introduced in [16] that relies on the computation of median posterior probability distributions. The algorithm is compared with existing consensus-based distributed PFs in terms of estimation accuracy, where it outperforms these methods in terms of robustness. Since the filter is attached with every sensor node, the technique causes heavy computation burden on sensor nodes.

Kalman in [22] proposed Kalman Filter (KF) that estimates the state of the control system. KF has less computational overhead and most suitable for noisy environment. KF is used with MLE (maximum likelihood estimation) [18] and with optical flow model [19] to estimate target location. In [20], the authors used the machine learning and KF based algorithm to track the target. Machine learning algorithm estimates the target's position using received signal strength indicators (RSSI) information. In the learning process, the kernel-based ridge regression and vector-output regularized least squares are used. The KF is used to combine predictions of the target's positions.

The gain values remain constant after the initial transits using KF. It is observed that the gain values have high impact on the filter estimation. Hence good tracking results can be achieved by optimizing the gain value. CGKF [23] applies genetic algorithm to compute optimal gain value. In existing filter based algorithm run KF [21] and CGKF [23] on CH or sensor nodes. It results in heavy computation burden on sensor nodes as they have limited battery and power supply. Table 1 summarizes the comparative study of target tracking algorithms in WSN. It is observed that the methods proposed in the literature are restricted to static BS model.

There are various applications in WSN where a need arises to collect data for mobile BS model [24]. In a military battlefield, a mobile BS model is attached to an unmanned aerial vehicle to detect enemy forces. The habitat monitoring is another example where a mobile robot is used to collect information from the nodes in the field to the targeted animal species.

The proposed hybrid EECGKFT algorithm runs CGKF [23] on BS to predict and estimate target location and reduces computational complexity. In parallel, selected sensor nodes calculate target location locally using trilateration algorithm. The proposed algorithm requires data transmission only when the precision of estimated prediction is beyond the threshold value. The proposed algorithm is analyzed for static and mobile BS model. It estimates target location correctly and provides good tracking results. By predicting future location the proposed algorithm also solves the boundary problem.

3. Proposed EECGKFT Algorithm

The proposed Energy-Efficient Constant Gain Kalman Filter based Tracking (EECGKFT) algorithm is based on clustering and prediction techniques. In the proposed algorithm, BS predicts the next location of the target by using Constant Gain

Table 1: Comparative study of target tracking algorithms in WSN.

Authors, year	Mechanism	Tracking accuracy	Energy consumption	Boundary node solution	Mobility of BS
Olule et al., 2007 [5]	Clustering	Less	Moderate	No	No
Dayana Pravin and Vijeyakumar, 2012 [6]	Clustering & prediction	Moderate	Low	No	No
Hosseini et al., 2013 [7]	Clustering & prediction	Moderate	High	No	No
Deldar and Yaghmaee, 2011 [8]	Clustering & prediction	Moderate	Moderate	No	No
Misra et al., 2015 [9]	Clustering & prediction	High	Moderate	No	No
Wang et al., 2010 [10]	Clustering	High	High	Yes	No
Hajiaghajani et al., 2012 [11]	Clustering	High	High	Yes	No
Hajiaghajani et al., 2013 [12]	Clustering	High	High	Yes	No
Akter et al., 2015 [13]	Clustering	High	High	Yes	No
Imran and Ko, 2017 [14]	Clustering & prediction	High	High	Yes	No
Vasuhi and Vaidehi, 2016 [15]	Prediction	High	High	No	No
Vázquez and Míguez, 2017 [16]	Prediction	High	Moderate	No	No
Jain et al., 2004 [17]	Prediction	Moderate	Moderate	No	No
Wang et al., 2012 [18]	Prediction	Moderate	Moderate	No	No
Shantaiya et al., 2015 [19]	Prediction	High	Moderate	No	No
Mahfouz et al., 2014 [20]	Prediction	High	Low	No	No
Karthika and Ramalakshmi, 2013 [21]	Clustering & prediction	Moderate	High	No	No

Kalman Filter (CGKF) [23]. It sends target predicted location (PL) to the CH that is closer to the target. Then three other sensor nodes near to the target are selected and activated by the CH for tracking. At these local sensor nodes, trilateration algorithm [13] is used for target localization in our proposed approach. Among these three sensor nodes, two nodes send their distance to the leader sensor node. The leader node is selected by the CH that has a higher selection parameter. The selection parameter is a ratio of energy (E) and distance (d) [12]. Leader node uses trilateration algorithm to locate the target and send current location (CL) of the target to the CH. The CH has two pieces of information: (i) the PL received from BS and (ii) the CL value received from the leader node. If the difference between these two values is out of the precision (i.e., greater than the threshold value), then only transmission takes place from CH to BS. In such case the CH sends CL values of target to the BS so that the BS has the correct and updated value of the target location. If the difference is not beyond the threshold value, the BS stores its PL values as a target location. Such case does not require any data transmission from the CH to the BS. Thus proposed algorithm reduces energy consumption by reducing data transmission. The system assumptions and pseudocode of proposed algorithm are shown in the following.

3.1. System Assumptions

(1) We assume that all the nodes are randomly distributed and stationary. Once the network is deployed, nodes can not change their positions.

(2) At the time of network deployment all sensor nodes are in sleep state except CHs. The CHs have higher energy compared to other sensor nodes.

(3) Initially other sensor nodes have same energy level and BS has large amount of energy.

(4) The BS is a resourceful node. It has information about the location of each node and their initial residual energy.

(5) Single hop communication model is used in proposed algorithm [25].

3.2. Pseudocode

(1) Let S be the set of p sensor nodes deployed in a given sensor network and BS is located at (50, 50) coordinate in the WSN.

$$S = \left\{S_1, S_2, S_3, \ldots, S_p\right\}. \tag{1}$$

(2) IF target is detected within the sensing range of sensor node, that sensor node sends initial location to the BS through CH.

(3) BS predicts next location x_{k+1} (PL) of target using CGKF.

$$\text{Cost}\left(k_k, r\right) = \frac{1}{N}\sum_{k=1}^{N}\left(v_k r {v_k}^T + \log|r|\right) \tag{2}$$

$$v_k = z_k - H_k x_k \tag{3}$$

$$x_{k+1} = x_k + k_k v_k, \tag{4}$$

where r represents the measurement noise which is randomly generated; N is a number of reference positions; and v_k is innovations sequence given as a linear

difference of measurements and its estimate. Here z_k is the measurement of the true state x_k at time k. Once the optimal gain k_k has been computed using genetic algorithm in which the cost function is used as mentioned in (2), the CGKF predicts target next location and update the state based on (4). The observation model H_k [18] is given as $\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$.

(4) BS sends predicted location (PL) to the active CH. Active CH selects three sensor nodes (S_q) nearer to the target's PL.

$$S_q = \{S_{q1}, S_{q2}, S_{q3}\}, \quad S_q \subseteq S. \tag{5}$$

(5) CH selects leader node $S_L \in S_q$ having higher selection ratio (R) of residual energy (E) and distance (d) from the target.

$$R = \frac{E}{d}. \tag{6}$$

(6) Selected nodes $\{\forall S_q \mid S_q \in \{S_{q1}, S_{q2}, S_{q3}\} \;\&\; S_q \neq S_L\}$ calculate their d from the target and send it to the leader node S_L.

(7) Leader node (S_L) calculates target's current location (CL) using trilateration algorithm using information received from two selected sensor nodes and its own sensed data. The calculated CL is sent to the CH.

(8) The active CH calculates difference between PL and CL. It compares it with a predefined threshold (δ) value.

If $|\text{PL} - \text{CL}| > \delta$
    CH sends CL to the BS.
Else
    No data transmission from CH.
    BS stores the PL.
End if.

(9) Repeat steps (3) to (8) until target is found within the network sensing area for every 0.5 seconds.

4. Experimental Setup and Results Analysis

This section presents the results of numerical experiments. The performance of above-mentioned pseudocode was evaluated using MATLAB for a static BS model and also for mobile BS model. We have used Radio Hardware Energy Dissipation model [26] for the energy calculation to transmit and to receive the data. Many researchers have used this model to simulate their algorithm [13, 21, 23]. We have considered network scenario as shown in Table 2. The evaluation of the proposed algorithm is based on the following three different parameters:

(i) Tracking accuracy in terms of RMSE (Root Mean Square Error)

(ii) Network residual energy

(iii) Network lifetime

Table 2: Simulation parameters.

Experimental parameters	Values
Field size	$100 \times 100\,\text{m}^2$
# of sensor nodes	{100, 200, 300, 400}
Static BS location	(50, 50)
Initial energy (E_i)	0.5 J
Threshold (δ) [6]	1 m
Target's speed	0–10 m/s
Sensing range	15 m
Communication range	30 m
Speed of BS movement	2 m/s

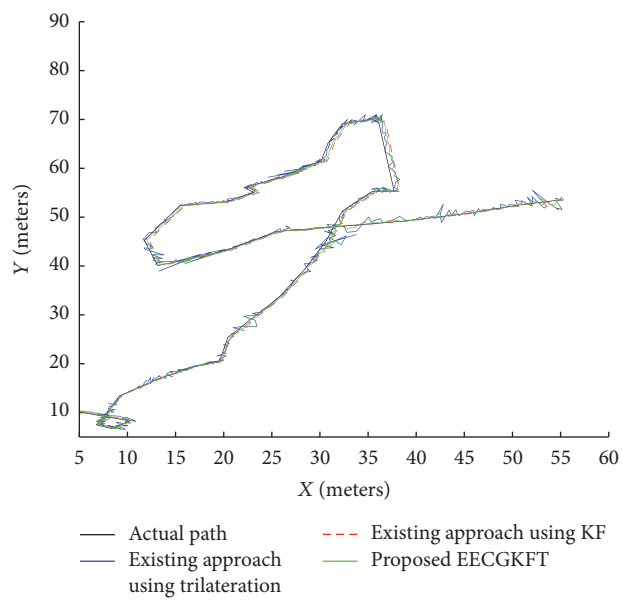

Figure 1: Path estimation.

4.1. Results Analysis for Static BS Model. We measure the performance of proposed algorithm based on path estimation accuracy. Figure 1 depicts that proposed EECGKFT gives best location estimate as compared to the existing localization algorithms [13, 21]. A part of the target trajectory is enlarged and shown in Figure 2 to have a closer look on the accuracy of the tracking.

Trilateration algorithm gives best estimate for exact range measurement. But it is not possible in the case of real-world because of environmental noise [27]. So the estimation of trilateration algorithm contains noise; hence proposed EECGKFT gives better estimate as compared to trilateration algorithm. In the proposed approach, the performance is better because the CGKF optimize the noise value (step (3) of the pseudocode) by finding the constant gain using genetic algorithm. RMSE of EECGKFT is reduced as compared to the trilateration algorithm and KF. Table 3 shows the RMSE analysis of trilateration, KF, and EECGKFT.

During the target movement in a network of 100, 200, 300, and 400 nodes, we have analyzed the behaviour of the network in terms of energy utilization. The Radio Hardware

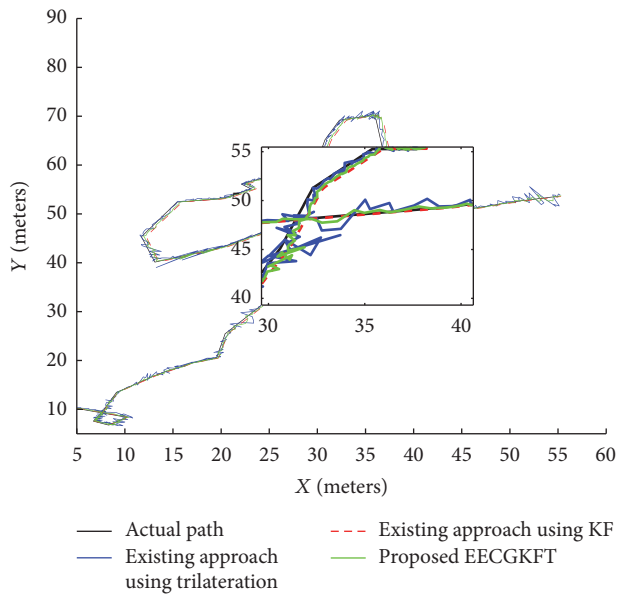

Figure 2: Path estimation (a part of the path is enlarged).

Table 3: RMSE analysis of trilateration, KF, and EECGKFT.

Estimation algorithm	RMSE
Existing approach using trilateration [13]	19.78%
Existing approach using KF [21]	12.05%
Proposed EECGKFT	1.03%

Energy Dissipation model is used in the proposed approach to calculate the transmitting and receiving energy [26]. Figure 3 shows the network residual energy for the period of first 50 sec of the target tracking in a network of 400 nodes. Simulation results show that the proposed algorithm reduces energy consumption. The improvement in the energy usage is achieved due to the prediction algorithm (CGKF) which runs at the BS. It helps in reducing data transmission from CH to the BS. The CH requires to forward data only when the precision of the PL of the target is more than the threshold. The threshold value for the proposed technique is set as 1 m. It can be derived from Figure 3 that the proposed algorithm has more network residual energy as compared to the existing techniques.

The proposed algorithm is also analyzed by comparing network lifetime. The network lifetime is extended when we apply the proposed algorithm as compared to existing algorithms. Figure 4 presents network lifetime for the different density of nodes in a WSN. We have considered the network lifetime till 5% of total nodes die (k-of-n lifetime T_n^k metric) [28].

4.2. Results Analysis for Mobile BS Model. We also measure the performance of proposed algorithm when BS is moving dynamically on predefined path. Tracking accuracy is not affected because location of BS is not playing any role in the proposed algorithm. Since the proposed algorithm operates with a single hop communication model, routing will also

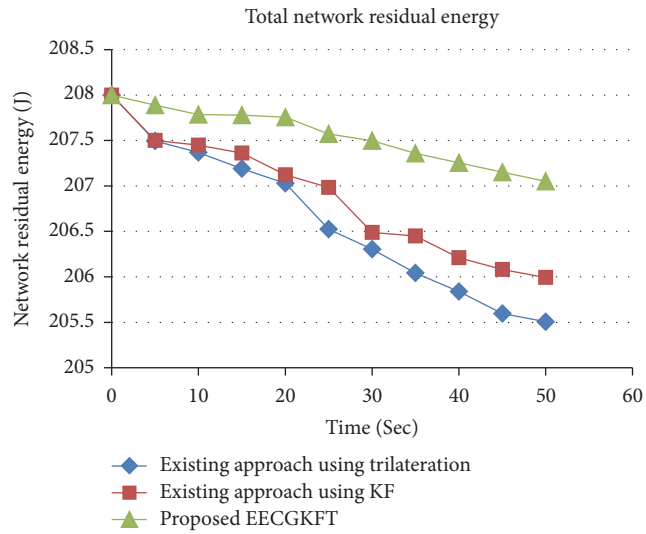

Figure 3: Network residual energy (400-node network).

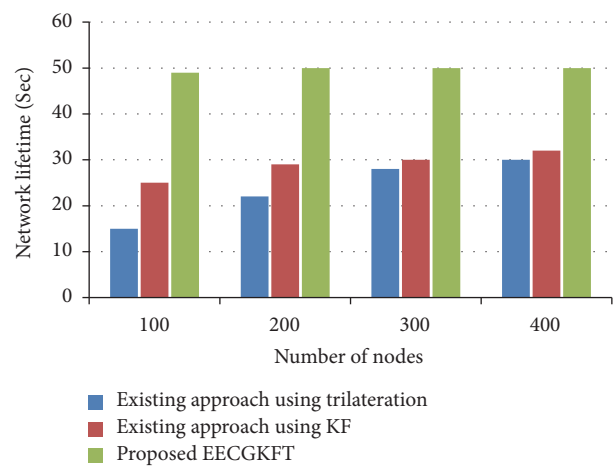

Figure 4: Network lifetime (5% of nodes die).

not be affected. Moreover, the energy consumption will not vary drastically due to BS's movement. The comparative analysis of network residual energy and network lifetime with node size 400 is shown in Figures 5 and 6, respectively, for mobile BS. Figure 5 depicts that network residual energy of proposed algorithm is not affected because of BS movement. The performance of the proposed algorithm outperforms and extends the network lifetime as compared to the existing algorithms. Due to BS movement, the lifetime of network is not affected in the proposed algorithm.

5. Conclusion

This paper presents novel approach for target tracking by combining clustering and prediction based techniques to improve lifetime of WSN. In addition, the proposed algorithm also provides accurate trajectory tracking by minimizing the RMS error. The proposed technique becomes computationally light weight and gives more accurate results.

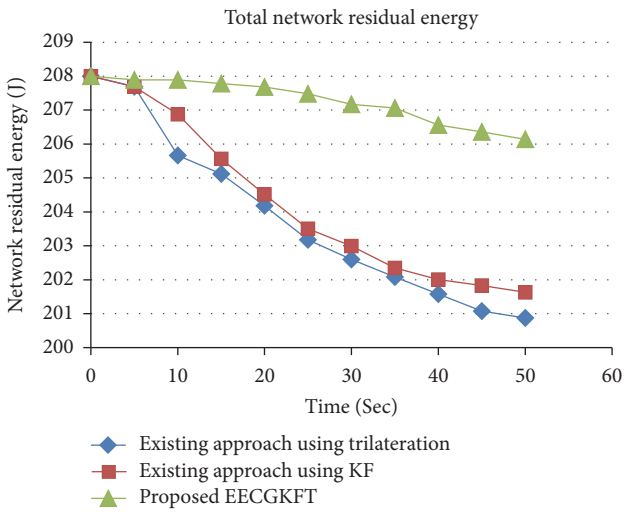

Figure 5: Network residual energy (400-node network).

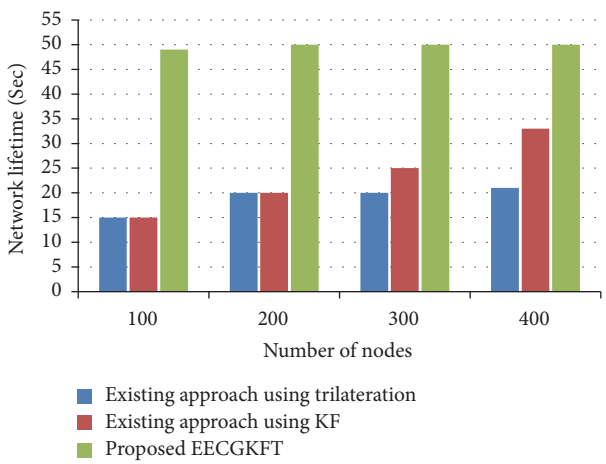

Figure 6: Network lifetime (5% of nodes die).

Simulation results show that the proposed algorithm improves the path estimation accuracy up to 18.75% and 11.02% compared to trilateration technique [13] and KF [21], respectively. It also provides energy-efficient solution for static BS model and for mobile BS model. The numerical and graphical results presented here conclude that the proposed technique outperforms the existing techniques in terms of energy efficiency by reducing redundant data transmission and extends the lifetime of network.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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