Accurate Target Tracking using Kalman Filtering and Location Estimation in Wireless Sensor Networks

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Abstract: ***Wireless Sensor Networks (WSNs), is one of the most emerging technologies in recent years. Target tracking and location estimation is one of the most important tasks in wireless sensor networks. Target tracking using Bayesian filtering technique doesn't concentrate much on filtering of noise in the signals. This reduces the accuracy of the target information. This paper addresses a Kalman filtering technique with prediction-correction step to remove the noise from a signal and to generate optimal estimate of desired quantities with the given set of measurements. Also it concentrates on location estimation of the sensor nodes in the network. The proposed Kalman filtering technique supports to solve the problem of trajectory estimation. Simulation results show that minimizes the energy consumption, missing rate, and localization error of the sensor nodes in the network.***

Keywords: Bayesian filtering, Correction, Kalman filtering, Prediction, Target tracking.

1. Introduction

A wireless sensor network is a collection of sensing nodes organized in a desired area that form a network with wireless links. They are capable of detecting, measuring, collecting, and processing the data they observe. Wireless Sensor Networks consists of several tiny sensor nodes that are deployed in any physical environment. These sensor nodes have been used to play a major role in the applications of industrial monitoring, agriculture, area monitoring, environmental/earth monitoring, structural monitoring, passive localization and tracking in the recent years. These applications require target tracking for the events of concern that takes place in an environment. Target tracking in WSNs has several merits like the (i) qualitative and fidelity observations (ii) processing signal accurately and timely and (iii) increased system robustness and tracking accuracy. The major challenges faced in target tracking algorithm is the consideration of the transaction or the tradeoff between the tracking accuracy and network resources such as energy, bandwidth and communication or computation. However the sensed data are futile without the sensor location information, mainly when used for tracking or other purposes [6]–[9]. If the sensors are limited to a small area exactly then the moving target object can be trailed in a better fashion. This location information of sensors is well watched by the moving target in the network. That is, sensor localization and target tracking balance each other.

A wide-ranging stipulation of SLAT is considered in our paper. The inhabitant location of sensors is distributed randomly roughly around their deployment points due to the extensively varying environment aspects and deployment errors. After the sensors are deployed, it exchanges data with the nearby sensors that lie within their communication ranges r_c. A set of data observation is thus collected and used to localize them in prior, improving the coarse *a priori* position information. The SLAT procedure defines the time at which a mobile target X_t enters into the Wireless Sensor Network. The mobile targets randomly move about through the environment without any restriction on its path or velocity. At the sampling instant t, only the sensors that sense the presence of the target X_t can form an activate cluster S_t for additional signal processing. The temporal observation between the target and each activated sensor is integrated in order to modernize the target temporal assessment. With regard to the activated sensor, the temporal observation of the target is used in combination with the static observation set that is stored during the prelocalization phase to refine its location estimation. Hence, the sensors that have detected the target are localized together with the tracking of the target.

The proposed Kalman filtering for concurrent localization and tracking algorithm provides an well-organized computational way to calculate approximately the state of a process, in a way that reduces the average of the squared error. The filter is extremely powerful in numerous aspects: it supports estimations of past, present, and even future states, and it can do so even when the exact temperament of the modelled system is indefinite.

The remainder of this paper is organized as follows. In Section II, we summarize the related work. In Section III, the system model is defined. The Kalman Filtering technique is described in detail in Section IV. The performance of the proposed Kalman Filtering method is evaluated through the simulations in Section V. Section VI concludes this paper.

2. Related Work

In the earlier work, the interdependent target tracking [2] that provides range measurements between the sensors and the target, sensor location estimations and that of the target are interdependently enhanced. This work relies on three aspects: firstly, the algorithm operates on a fully decentralized cluster technique; secondly, a general state evolution model is proposed in order to describe the target and activated sensors, since a priori information of the target motion is not obtainable at hand finally, the variational method further mitigates the communication overhead. Simultaneous Localization and tracking [11] with Laplace approximation avoids computational intricacy. Measurement noise is involuntarily averaged out improving the localization and the tracking precision in high-traffic region. The filtering framework integrates measurements in petite batches, providing online estimates of almost all the locations, calibration parameters and their uncertainties. But this algorithm is put into operation in a centralized implementation and it requires multiple hops to transmit data to the central computer. Hence, the energy and bandwidth cost of centralization increases. Simultaneous localization, mapping and moving object tracking [3] involves both simultaneous localization and mapping in dynamic environments. It is also involved in detecting and tracking these dynamic objects. Two algorithms are described in order to combine SLAM with widespread objects as well as with the detection and tracking of objects that move. It is computationally challenging and normally infeasible. With regard to the sensor localization crisis, sensor nodes do not require support from other positioning systems such as the Global Positioning System (GPS) in this technique. Node localization along with GPS free localization is known as the Matrix transform-based Self Positioning Algorithm MSPA [4]. This is where the job is to exploit the distance information between nodes to decide on the coordinates of static nodes in 2D or 3D space. One important issue in GPS-free localization algorithms is the basic performance impact of several parameters. RSS-based cooperative localization [5] method that approximates unknown coordinates of sensor nodes in a network. A co-operative localization technique that adds in estimations from multiple fixed reference nodes is open to presentation in order to enhance the precision of the localization. A strong correlation is integrated in analyzing the comparative positions between two sensor nodes by making use of the received signal strength indication (RSSI) model. Power Adaptive Localization Algorithm [6] utilizes the RSS data from the beacons or the neighbouring nodes to understand the position of the node concerned without requiring any additional hardware instruments. It cannot be frankly applied to the sensor networks with numerous transmit-power levels. In the Beacon-less location discovery method [7], each sensor initially discovers the number of its neighbours from each group. This is the surveillance of a sensor. Using this surveillance data, a sensor thus estimates a location which is based on the principle that the estimated location should make the best use of the probability of the observation. KPS relies on the sharing of the node exploitation. Therefore, once a node moves, the distribution cannot be sustained. KPS can only be used in an immobile sensor network. Locations of deployment points are vital.

3. Kalman Filtering For Accurate Target Tracking And Localization

Problem Definition

The preliminary assignments of sensors are deployed arbitrarily in the area of their deployment points. The final inhabitant location S^i of sensor i is supposed to be Gaussian disseminated in the region of its deployment point $S^{-i}$with exactness η^i i.e. $S^i \sim \mathcal{N}(S^{-i}, \eta^i)$. Subsequent to the deployment phase, the sensor i exchanges its information with its neighbouring sensors in the transmission range r_c, which is indicated by the red dashed circle in Fig. 1 [1]. To advance the coarse *a priori* information which is on the sensor location, a prelocalization phase is commenced by adding in these dimensions, i.e.

$$\rho(\hat{S}^i | Z^{i,s}) \propto \mathcal{N}(S^{-i}, \eta^i) \prod_{\|S^i - S^j\| \leq r_c} \rho(Z^{i,j} | S^i). \qquad (1)$$

The supplementary specific information of sensor location is thus made available with this prelocalization phase. Fig. 1 indicates the distributive cluster base model to decrease the bandwidth and energy consumption. Once the target comes into the WSN, the cluster of sensors S_t is triggered. Only the sensors which sense the presence of the target x_t form an activated cluster S_t. As shown in Fig. 1, sensors that sense the target x_t are in the blue dotted circle with the center x_t and the radius r_s. The range of a cluster is resolved by the association between the communication range r_c and the sensing range r_s. For localization accuracy and energy efficiency, the communication range is defined as double the sensing range (r_c= $2r_s$), which assures that a single cluster is formed at each moment and the communication in the activated cluster is within a single hop.

The activated sensors broadcast their remaining energy level to all other sensors in the cluster. The sensor with the maximum residual energy is chosen as the cluster head (CH) to take control of signal processing. The other clustered detecting sensors then transport their observations to the CH. These observations comprises of the subsequent two parts which are: 1) the temporal observation amongst the clustering sensors and the target, i.e.$Z_t^{s,x} = \{Z_t^{i,x}\} \forall s^i \in S_t$, which is included to keep informed about the target temporal estimation, and 2) the static observation that is stored during the prelocalization phase, which is integrated with the temporal observation $Z_t = \{\{Z^{i,s}\} Z_t^{s,x}\}$ where m_t is the number of activated clustering sensors, to further refined their position estimations. Hence, approximations of the target and the detecting sensor locations are concurrently updated in the CH based on these observations.

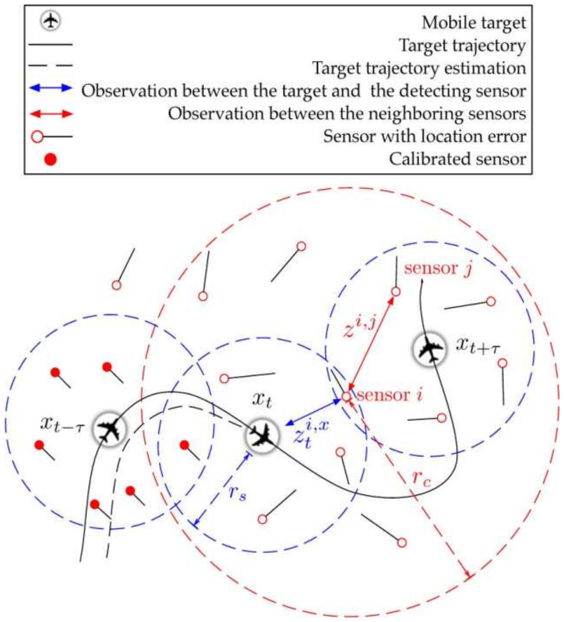

Figure 1: SLAT scenery [1]

The prediction phase utilizes the state estimate from the earlier sampling moment to create an estimate of the state at the existing instant according to

$$p(\boldsymbol{X}t|\boldsymbol{Z}1{:}t-1)=\int p(\boldsymbol{X}t|\boldsymbol{X}t-1)p(\boldsymbol{X}t-1|\boldsymbol{Z}1{:}t-1)\,d\boldsymbol{X}t-1.$$

In prediction phase, with the prior position of the target x_{t-1} and the sensors in activated cluster $\{s^i\}$i=1 to mt the sensors that sense the next location of the target x_t. After the cluster is activated, the sensors that predict the next location of the target are compared with previous target position and sensed information from the cluster.

Fig 2 illustrates the corrector-predictor step of the Kalman filtering technique. In the prediction step involves the time update being taken where the one-step ahead prediction of observation is computed**.**

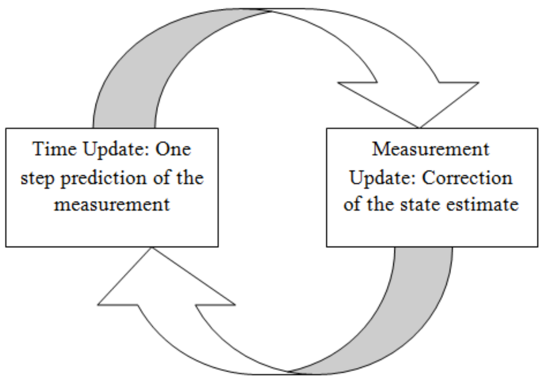

Figure 2: Schematic illustration of Kalman filter's update as a predictor-corrector

In the correction step, the measurement update is observed where the correction to the estimate of current state is computed i.e. the measurement update regulates the projected estimate by a genuine measurement at that time.

(i)The time update equations are accountable for projecting forward the current state as well as the error covariance estimates to gain the a priori estimates for the next time step.

(ii)The measurement update equations are responsible for the feedback i.e. for incorporating a new measurement into the a priori estimate to obtain an improved a posteriori estimate.

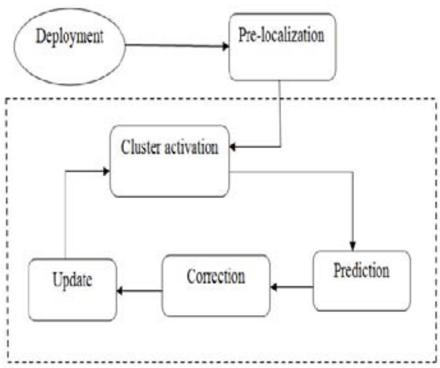

Figure 3: Architecture Diagram

In the update phase, measurement data at the current instant is used to refine this prediction to appear at a new and more accurate state estimate.

$$p(\boldsymbol{X}t|\boldsymbol{Z}1{:}t) = \frac{p(Zt|Xt)p(Xt|Z1{:}t-1)}{p(Zt|Z1{:}t-1)}. \qquad (2)$$

Where,

$$p(\boldsymbol{Z}t|\boldsymbol{Z}1{:}t-1) = \int p(\boldsymbol{Z}t|\boldsymbol{X}t)p(\boldsymbol{X}t|\boldsymbol{Z}1;t-1)d\boldsymbol{X}t.$$

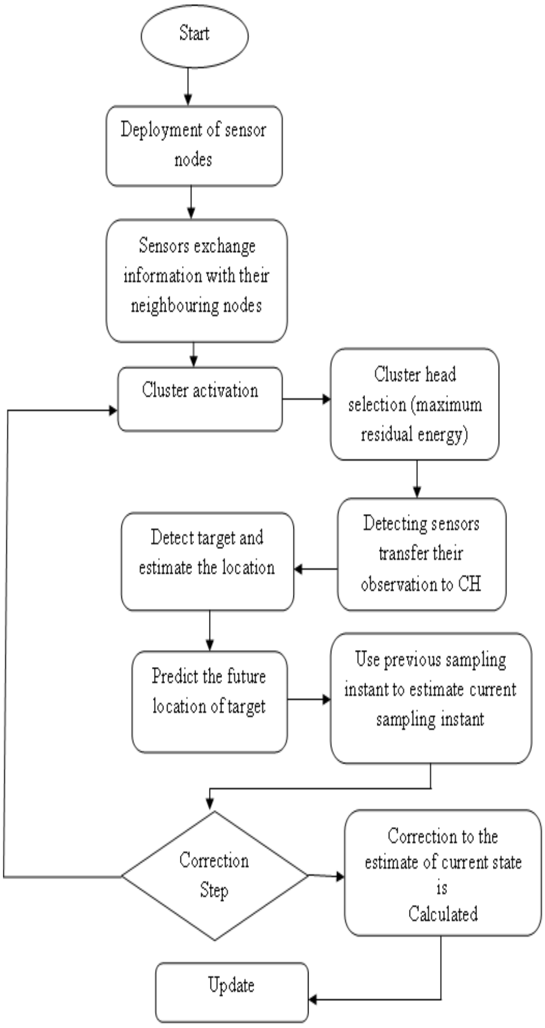

Figure 4: Flowchart of Kalman Filtering.

In update phase, the predicted location x_t and the sensed observations $\{z^{i,s}\}, \{z_t^{s,x}\}$ are updated. The cluster is formed based on the updated information with the neighbouring sensors of the predicted next target location.

The initial task for the duration of the measurement update is to calculate the Kalman gain. After each time and measurement update pair, the process is recurred with the previous a posteriori estimate that is used either to project or to predict the new a priori estimates.

4. Simulation Results

Fig 5 indicates the comparison of SLAT, DVaSLAT and Kalman filter models' localization error. Kalman filter that shows the minimized localization error when compared with SLAT and DVaSLAT model.

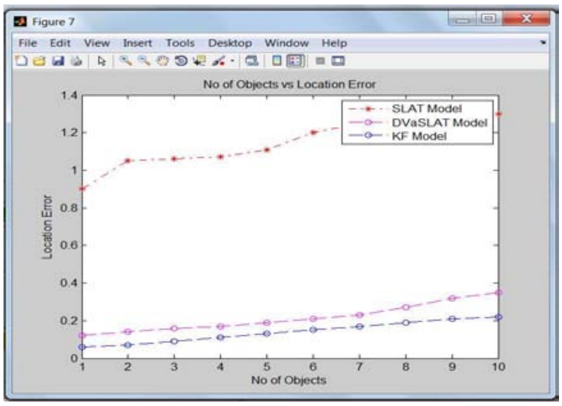

Figure 5: No of objects vs location error

Fig. 6 demonstrates the comparison of SLAT, DVaSLAT and Kalman filter models' missing rate. The proposed Kalman filter model shows the minimum level missing rate compared to SLAT and DVaSLAT models.

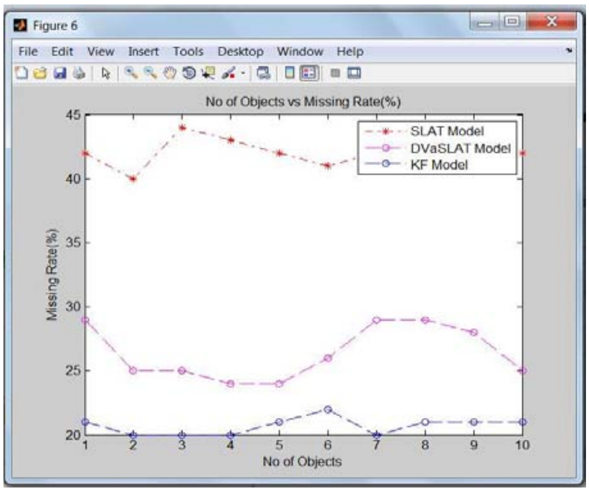

Figure 6: No of sensors Vs Missing Rate

5. Conclusion

Simultaneous Sensor Localization and Target Tracking in Wireless Sensor Networks using Kalman Filtering have been proposed in the context of WSN. Without any prior information on the target movement, the DVaSLAT algorithm aims at incessantly updating and enhancing the estimates of the activated sensor locations and the target trajectory. To reduce the resource expenditure in WSNs, the DVaSLAT algorithm is operated on a fully distributed cluster technique. That is, only the sensors that have detected the target are triggered to form a cluster to process data. The variational method permits an implicit compression of the exchanged data between clusters, which significantly decreases the inter cluster communication. To conclude, as the target freely moves in WSNs, a large number of range measurements are created, which makes it possible for both the activated sensors' localization and the target tracking. To add noise filtering to the DVaSLAT algorithm, Kalman filtering technique is used. Simulation results have shown that the accuracy of tracking the target is obtained at an increased level.

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