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RESEARCH ARTICLE

Localization in Mobile Sensor Networks using Kalman Filter

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Abstract

Objectives: The objectives of this study is to propose a localization scheme that meets the requirements of Mobile Sensor Networks (MSNs) in terms of high localization accuracy, lower power consumption and high network coverage. **Methods**: In this study, a localization scheme has been proposed to allow sensor nodes to estimate their locations using information transmitted by a set of anchor nodes that know their own locations. The proposed scheme performs localization process in a more general network environment where no special hardware for ranging is available, the prior deployment of anchor nodes is unknown, the anchor nodes density is low, the node distribution is irregular, and where sensor nodes and anchors can move uncontrollably. The proposed scheme applies the Kalman Filter (KF) technique to combine the information from anchor nodes to estimate the location of sensor nodes. The KF takes into account the different uncertainties and error sources that disturb the localization process. **Findings:** The proposed scheme has been compared with the two classes of Flexible Optimal Kalman Filtering FOKF algorithm (FOKF-O and FOKF-R) under different mobility models and extensive simulations in large scale network. The results show that the proposed scheme has a lower localization error and lower communication cost than the FOKF algorithm which leads to maximizing network lifetime and energy saving. The proposed scheme has an improved percentage of localization accuracy than FOKF-O and FOKF-R by 5.0% and 4.0% respectively, also it has an improved percentage of coverage than FOKF-O and FOKF-R by 10.0% and 5.0% respectively, finally it has a less number of transmitted beacon messages than FOKF-O and FOKF-R by 171 and 113 packets respectively which leads to maximizing network lifetime. **Novelty/Applications:** The proposed scheme is considered a suitable localization solution for resource-limited sensor nodes in terms of memory limitations, energy consumption and localization accuracy.

Keywords: Localization; Mobile Sensor Networks; Kalman Filter; FOKFO; FOKFR

1 Introduction

Mobile Sensor Networks have been established as a result of the cooperation between Wireless Sensor Networks (WSNs) and Robotics [1]. Nowadays there has been an increasing interest in the creation of MSNs and they are the preferred aspect of WSNs in which mobility plays an important role while an application is going to execute. Location awareness is required by many sensor network applications, but using a GPS receiver in a sensor network nodes is often too expensive [2]. Recently some localization schemes have been proposed to allow sensor nodes to estimate their locations using information transmitted by a set of anchor nodes also most of the recent research focuses on the minimization of localization errors during the localization process but most of them suffer from one or both of these problems: Depending on special devices like measuring ranging information from signal strength, time of arrival, time difference of arrival or angle of arrival which require hardware that is typically not available on sensor nodes. Adding the required hardware increases the cost and size of the nodes. The other problem is Requirement for specific network topologies where most schemes require large number of deployed anchor nodes and uniformly distributed so they can cover the whole network. But prior deployment of anchors or map of particles are not possible in many sensor network applications [3].

Therefore, there is a need to develop a localization algorithm that avoids these problems and fulfills MSNs requirements and sensor nodes specifications. Hence, this study concerned with carrying out localization in more general environment where no special hardware devices for ranging is available, unknown prior deployment of anchor nodes, the density of anchor nodes is low, the deployment of sensor nodes is irregular, and where sensor and anchor nodes can move uncontrollably. The proposed scheme takes advantage of mobility to improve localization accuracy, having less number of anchor nodes and obtaining the probabilistic distribution of a possible positions for sensor nodes covered by a number of anchor nodes. Prior location information is required to obtain an accurate localization but it will become increasingly inaccurate when sensor node is moving. Hence, the proposed scheme takes new observations from anchor nodes (GPS measurements which are prone to errors due to various sources) then integrating Kalman filter technique to filter impossible locations which reduces localization error then determine the posterior distribution of the sensor nodes possible positions after movement.

The proposed scheme has a linear state and measurement equations so that the relation between them need not to be transformed by Jacobean matrix, i.e. every element in the measurement vector is related directly to its corresponding element in the state vector [4]. There are three different simulation models of Kalman filter: **P**, **PV** and **PVA** (Position/Velocity/Acceleration) which are used in the object tracking or in sensor localization. In this study, the proposed scheme is based on measuring position and velocity of sensor node so that the first model **P** (Position) was rejected. According to the second and third models **PV** and **PVA**, the **PV** model is chosen instead of **PVA** model because sensor node moves with constant velocity at a time (acceleration = 0), also, **PV** has less computation time and lass memory requirements which are considered an important factor in power consumption in sensor nodes. These comparisons are illustrated in Table 1.

Table 1. Computation Complexity of Kalman Filter Models

KF Model	Computation Complexity	Size of state vector
P	$O(n^3)$	n = 2
PV	$O(n^3)$	n = 4
PVA	$O(n^3)$	n = 6

The inclusion of measurements into state estimates is determined by the Kalman Gain (KG), influenced by the uncertainty in the prior state estimate and the uncertainty in the measurement estimate. Intuitively, measurements with high precision should result in precise state estimates. The measurements measure the full state, and thus if they have high precision, the proposed scheme can count on them as good indicators for the true state and the Kalman Gain should reflect this.

As show in Figure 1, the higher the prior uncertainty, the more the KG moves towards one. The higher the prior uncertainty, the less confidence the proposed scheme has in the state estimate and thus the more it wants to take information from the real world. On the other hand, the measurement noise tries to lower the Kalman Gain. Higher uncertainty in the measurements indicates that the information from the real world is not that trustworthy and that thus less of the information should be taken into account. Hence, the proposed scheme balances these two uncertainties by the resulting Kalman Gain.

The rest of this article is organized as follows: Section 2 provides the related works according to Kalman filter localization in WSNs. Section 3 illustrates the proposed scheme. Section 4 provides the performance evaluation of the proposed scheme compared with the two classes of Flexible Optimal Kalman Filtering algorithm (FOKF-O and FOKF-R) under different mobility models and extensive simulations in large scale network using different performance metrics. Finally, section 5 presents the study conclusion.

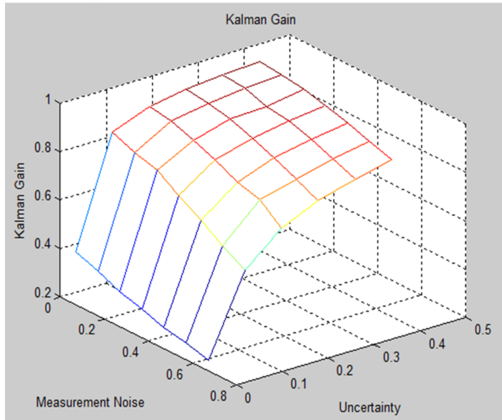

Fig 1. Impact of Kalman Gain

2 Related Works

Yan Wang et al.[5] proposed a localization scheme based on robust extended Kalman filter and track-quality-based (REKF-TQ) fusion algorithm. This scheme mainly proposed for reducing the effect of the non-line of sight errors (NLOS). Simulation results of this scheme provides better localization accuracy than the EKF and REKF in the NLOS environment. Authors in[6] proposed a Reinforced ABC-EKF algorithm, this technique is based on big data blending technique to validate the localization error. This algorithm tries to removes a vulnerable position because it has an inaccurate value. The work presented in[7] proposes a method to decrease the influence of NLOS environment. In this work, a propagation model between anchor nodes (ANs) and mobile nodes (MN) is identified then adapt Kalman filter technique to filter the measurement errors.

Xuming Fang et al.[8] proposed a localization scheme based on a novel third-order adaptive cubature KF (ACKF) with higher estimation accuracy. The proposed scheme is a noise-aware algorithm which improves the accuracy of the existing schemes by up to 63%. Authors in[9] proposed a switching extended Kalman filter bank (SEKFB) algorithm which is used for indoor WSN localization where the problem of uncertain process-noise covariance has been alleviated. When using the constant-velocity motion model for indoor localization, this problem appears but there are a number of extended Kalman filters (EKFs) run in parallel using a set of covariance hypotheses, and the most likely output obtained from the EKFs is selected using Mahalanobis distance evaluation so as to overcome this problem.

The work presented in[10] concerned with the local monitoring of air pollution. The proposed system tries to improve a high-performance wireless sensor networks for this purpose which is enabled by the Internet of Things (IoT) sensor nodes collocated in a redundant configuration for gathering and transferring air quality data. In order to improve the accuracy of this system, an extended fractional-order Kalman filtering (EFKF) has been used to assimilate and recover the missing information. Yufang Yin et al.[11] proposed a method for distributed location estimation in the wireless sensor network based on the Bayesian sensor fusion mechanism. In this method, a fusion center collects local calculation of target position transmitted by sensor nodes, afterwards a fusion center generates the final estimated trajectory under a Bayesian system. This work applied unscented Kalman filter for each sensor node to compute local estimation using received signal strength indication-based approach.

Authors in[12] proposed a polynomial fitting-based adjusted Kalman filter (PF-AKF) method, which is robust to NLOS errors. The proposed method does not require any prior statistical information of the NLOS noise. The simulation results show that the proposed method is robust to the NLOS errors with higher localization accuracy, and the method has better performance when the measurement noise is small. Nevertheless, this method suffers from computational complexity and degradation in performance. The work presented in[13] proposes a fully distributed localization algorithm named constructed neighborhood Kalman filter (CNKF). It is a fully distributed algorithm where each sensor node only cooperates with its neighboring sensor nodes to get the localization with noisy distance measurements. The algorithm is easily implementable for large-scale networks and can make full use of the intra-network information. The situation results show that the proposed algorithm is effective and suitable for the wireless sensor networks. The CNKF uses the first-order approximation to model the nonlinear measurement. So, the iterations may be hard to converge if the error of initial guess is large.

According to[14], the authors have analyzed the performance of EKF localization. However, to the best of the authors' knowledge, the performance of such models under localization has not been considered yet. The localization results of the EKF are analyzed and compared with the results of different localization algorithms. More specifically, the proposed localization algorithm presents good accuracy in terms of cross-sectional area, distance, localization coverage, etc., but still has computational complexity. Authors in [15] proposed a fast implementation of linear Kalman filter on a high frame-rate tracking system where a Newtonian model was taken into account to track each fiducial of a surgical tool individually. This technique efficiently suppresses acquisition and estimation noise experienced by an optical tracking system. In addition, high performance in dynamic localization of intraoperative instruments proves that the proposed framework eliminates the requirement of rigid-body constraint while tracking a surgical tool at high temporal resolution.

The work in [16] derived the analytical expression for the localization of Unscented Kalman Filter (UKF) and Particle Filter (PF) algorithms. The derived expressions are coherent in the sense that under different situations they can be used to evaluate the approaches of localization. The proposed localization algorithms are compared with each other based on their performance and also with the EKF-based localization algorithm, however these algorithms are not compared with other localization algorithms. Besides this, the authors need to improve the localization performance of the EKF, UKF, and PF-based localization algorithms. The work presented in [17] is based on the distributed Kalman filtering in the presence of intermittent observations and different sensing states over the wireless sensor networks (WSNs). An adaptable flexible optimal Kalman filtering (FOKF) for variable sensing states has been developed using a class of flexible binary values. Hence, two classes of FOKFs algorithm haven been proposed including FOKF-O and FOKF-R. Simulation results show that they have high localization accuracy, strong robustness, low energy consumption.

This study proposes a range-free anchor-based localization scheme based on the Kalman filter to have high localization accuracy, lower communication cost, high coverage under varying mobility speed and different mobility models. The proposed scheme aims to have low power consumption, which saves the residual energy of sensor node, hence maximizing network lifetime. Simulation results show that the proposed scheme has a lower localization error, lower communication cost, lower power consumption and high coverage than FOKFs algorithms. The following sections provides the modeling and simulation processes of the proposed scheme.

3 The Proposed Scheme

This section provides the detailed steps for modeling the proposed scheme followed by the complete procedure of the Kalman filter.

3.1 Modeling the Proposed Scheme

As stated before, the proposed scheme enables mobile sensor nodes to determine their location based on beacons exchanged between anchor (1-hop and 2-hop) and sensor nodes. But using only this method will result in high localization error, thus the Kalman filter technique has been used to improve the localization accuracy as follows: the Kalman filter works in a two-step process: in the prediction step, the Kalman filter produces estimates of the current state variables, along with their uncertainties. Once the outcome of the next measurement (the measured position (ax, ay) taken from anchor nodes and the measured speed of sensor node) is observed, these estimates are updated (update step) using a weighted average, with more weight being given to estimates with higher certainty. Thus, the whole localization process is based on two stages, the first one is the **prediction** of system state and the second one is the **correction** of the predicted state according to the measured data. The measured speed of sensor nodes can be formulated according to the following formulas:

$$\dot{x} = \frac{d \times \cos(\theta)}{\triangle t} \tag{1}$$

$$\dot{y} = \frac{d \times \sin(\theta)}{\triangle t} \tag{2}$$

Where, $\dot{x}$ is the velocity of sensor node in x-component, $\dot{y}$ is the velocity of sensor node in y-component, **d** and θ is the moving distance and direction respectively of sensor node during slot duration $\mathbf{\Delta t}$. The predicted ($\mathbf{x}_k$, $\mathbf{y}_k$) position at slot **k** can be computed according to the following equations:

$$x_k = x_{k-1} + \triangle t \dot{x} \tag{3}$$

$$y_k = y_{k-1} + \triangle t \dot{y} \tag{4}$$

Where $(x_{k-1}, \mathbf{y}_{k-1})$ is the estimated position of sensor node at previous slot **k-1**. The Kalman filter averages a prediction of a system's state with a new measurement (position taken from the anchor nodes and measured speed) using a weighted average. The purpose of the weights is that values with better (i.e., smaller) estimated uncertainty, are trusted more. The weights are calculated from the covariance, which is proportional to the speed of the sensor node because there is uncertainty about the accuracy of the position predicted at high speeds but very certain about the position when moving slowly. The result of the weighted average is a new state estimate that lies in between the predicted and measured state, and has a better estimated uncertainty than either alone. This process is repeated every time slot **k**, with the new estimate and its covariance informing the prediction used in the following iteration. This means that the Kalman filter works recursively and requires only the last best guess not the entire history of a system's state to calculate a new state. The following subsections show how to model the Kalman filter according to the assumptions made above.

3.2 State Equation of the Proposed Scheme

Consider the state vector as $\mathbf{X}_k = [x_k\ y_k\ \dot{x}_k\ \dot{y}_k]^{\mathrm{T}}$,where x_k and y_k specify the position of sensor node, $\dot{x}_k$, $\dot{y}_k$ are the velocities in the Cartesian plane and $[x_k\ y_k\ \dot{x}_k\ \dot{y}_k]^{\mathrm{T}}$ is the transpose of the state vector. The dynamic system of sensor node can be modeled by linear kinematic with a discrete Wiener velocity model as follow:

$$X_k = \begin{bmatrix} x_k \\ y_k \\ \dot{x}_k \\ \dot{y}_k \end{bmatrix} = FX_{k-1} + w_k \tag{5}$$

$$F = \begin{bmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{6}$$

$$w_k \approx N(0, Q) \tag{7}$$

$$Q = \begin{bmatrix} \Delta t^3/3 & 0 & \Delta t^2/2 & 0 \\ 0 & \Delta t^3/3 & 0 & \Delta t^2/2 \\ \Delta t^2/2 & 0 & \Delta t & 0 \\ 0 & \Delta t^2/2 & 0 & \Delta t \end{bmatrix} * q \tag{8}$$

Where, $\mathbf{X}_k$ is the predicted state vector at time slot **k**, **F** is the state transition model which is applied to the previous state $\mathbf{X}_{k-1}$, w_k is the state noise which is assumed to be drawn from a zero mean Gaussian white noise with covariance $\mathbf{Q} = \mathrm{E}[w_k\ {w_k}^{\mathrm{T}}] = \sum w_k w_k$, and **q** fixes the spectral density of the noise.

3.3 Measurement Equation of the Proposed Scheme

This section figures out a noisy measurement (**ax**, **ay**) of the true position of the sensor node. Take $(\dot{x},\dot{y})$ as the measured velocity of sensor node at every time slot **k**, then the measurement vector is given by $Z_k = [\mathbf{ax}\ \mathbf{ay}\ \ \dot{x}\ \dot{y}]^{\mathrm{T}}$ and the measurement equation is:

$$Z_k = HX_k + v_k \tag{9}$$

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{10}$$

Where, **H** is the measurement matrix which maps the true state space into the measurement space. This model describes how measurements Z_k depend on the location $\mathbf{X}_k$ of sensor node. Where the measured position gives measurement Z_k of the location of the sensor node $\mathbf{X}_k$ corrupted by measurement noise $\mathbf{v}_k$. Assume that the measurement noise is zero on average, Gaussian distributed, and that it has a covariance **R** as given in the following equations:

$$v_k \approx N(0, R) \tag{11}$$

$$R = \left[\sigma_z^2\right] = \begin{bmatrix} \sigma_x^2 & 0 & 0 & 0 \\ 0 & \sigma_y^2 & 0 & 0 \\ 0 & 0 & \sigma_{\dot{x}}^2 & 0 \\ 0 & 0 & 0 & \sigma_{\dot{y}}^2 \end{bmatrix} \tag{12}$$

Where σ_x , σ_y, $\sigma_{\dot{x}}$ and $\sigma_{\dot{y}}$ are the deviation of the measurement covariance.

Kalman Filter Phases

The Kalman filter is a recursive estimator model. This means that only the estimated state from the previous time step and the current measurement are needed to compute the estimate for the current state. The Kalman filter can be conceptualized as two distinct phases: Predict and Update. The predict phase uses the state estimate from the previous time slot to produce an estimate of the state at the current time slot. This predicted state estimate is also known as the a priori state estimate because (although it is an estimate of the state at the current time slot) it does not include any measurement information from the current time slot. In the update phase, the current a priori prediction is combined with current measurement information to refine the state estimate. This improved estimate is termed the a posteriori state estimate. The following sub-section show how to apply the Kalman filter phases to the localization process.

3.4.1 Initialization Phase

According to mobile sensor network, there is no knowledge about the estimated position of sensor nodes in the first time slot **k = 0**, so that the Kalman filter initial conditions are given as shown below:

$$\widehat{X}_{0,-1} = 0 \tag{13}$$

$$P_{0,-1} = P_0 = \alpha I = \begin{bmatrix} \alpha & 0 & 0 & 0 \\ 0 & \alpha & 0 & 0 \\ 0 & 0 & \alpha & 0 \\ 0 & 0 & 0 & \alpha \end{bmatrix} \tag{14}$$

Where, $\widehat{X}_{0,-1}$ is the initial state estimate at time slot **k= 0**, $P_{0,-1}$ is the initial uncertainty at time slot **k = 0** and **I** is the unit matrix. Because there is no certainty about the initial position of sensor node, α is given as a suitable large number to give high uncertainty. Next, project the state estimate as follows.

3.4.2 Predict Phase

The time update (predict) equations are responsible for projecting forward (in time) the current state and error covariance estimates to obtain the a priori estimates for the next time step. The prediction formula is given by:

$$\widehat{X}_{k,k-1} = F\widehat{X}_{k-1,k-1} \tag{15}$$

Where, $\widehat{X}_{k,k-1}$ the predicted (a priori) state estimate at current slot **k** given $\widehat{X}_{k-1,k-1}$ which is the updated (corrected) state at previous slot **k-1** transformed by state transition model **F**. The prediction covariance matrix is given by:

$$P_{k,k-1} = FP_{k-1,k-1}F^T + Q \tag{16}$$

Where, $P_{k,k-1}$ is the predicted (a priori) estimate covariance (or uncertainty) at current slot **k** given $P_{k-1,k-1}$ which is the updated uncertainty at previous time slot **k-1** and **Q** is the process noise covariance matrix, which given in equation (8).

3.4.3 Measurement Update Phase

The measurement update equations are responsible for the feedback, i.e. for incorporating a new measurement into the a priori state estimate to obtain an improved a posteriori estimate. The measurement update equations can be thought of as corrector equations. The current a priori prediction $\widehat{X}_{k,k-1}$ is combined with current measurement information Z_k to refine the state estimate. This improved estimate is termed the a posteriori state estimate$\widehat{X}_{k,k}$. The measurement update phase consists of the following stages:

1. Calculate innovation or measurement residual matrix {\widehat Y}_k as given by the following formula:

$$\widehat{Y}_k = Z_k - H\widehat{X}_{k,k-1} \tag{17}$$

Where, $\mathbf{H}\,\widehat{X}_{k,k-1}$ is the measurement prediction

2. Calculate innovation (or error residual) covariance matrix S_k as shown below:

$$S_k \;=\; H\,P_{k,k-1}\,H^T \;+\; R \tag{18}$$

Where, **R** is measurement noise covariance matrix, which given in equation (12).

3. Calculate Kalman gain K_{gk} as shown below:

$$K_{gk} \;=\; P_{k,k-1} \;\; + H^T \;\, S^{-1}{}_K \tag{19}$$

4. Calculate the updated (a posteriori) state estimate $\widehat{X}_{k,k}$ as given below:

$$\widehat{X}_{k,k} = \widehat{X}_{k,k-1} + K_{gk}\widehat{Y}_k \tag{20}$$

5. Obtain the updated (a posteriori) estimate covariance $P_{k,k}$ as shown below:

$$P_{k,k} \;=\; (I - K_{gk}\,H)\,P_{k,k-1} \tag{21}$$

Where, **I** is the unit matrix. The complete procedure of the Kalman filter shown in Figure 2.

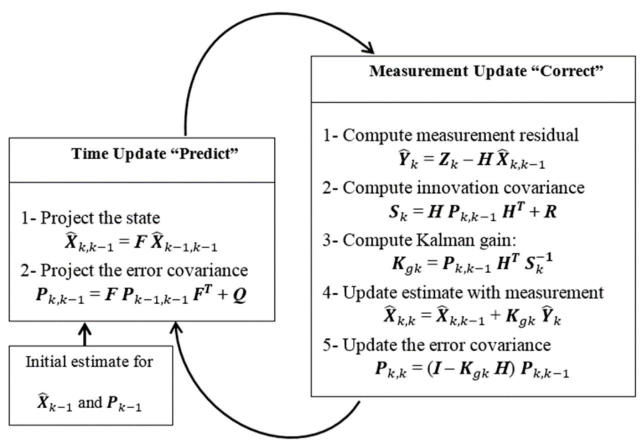

Fig 2. The complete procedure of Kalman Filter

4 Results and Discussion

In this section, the performance of the proposed scheme is compared with the two classes of Flexible Optimal Kalman Filtering algorithm (FOKF-O and FOKF-R) using WSN localization simulator [18]. The key metric for evaluating the performance of the proposed scheme is the accuracy of the location estimates or localization error, Coverage and communication cost. Simulation parameters used her are shown in Table 2.

4.1 Localization Accuracy

To study the localization accuracy, the total number of sensor nodes was set to 322 nodes, maximum speed $\mathbf{V}_{max} = \mathbf{R_c}$, where $\mathbf{R_c}$ represents the communication radius of sensor nodes, total number of anchor nodes is 28 nodes, simulation time = 30 time slots and Localization error is computed as a percentage of $\mathbf{R}_c$. As shown in Figure 3, the localization error starts by a large value due

Table 2. Simulation Parameters

Simulation Area	500 x 500 m^2
Sensor communication range	Rc = 50 m
Anchor communication range	Rc = 50 m
Mobility Model	Modified Random Waypoint
Moving Speed range	[0, V_{max}]
Maximum Speed	V_{max} = Rc/slot time
Number of sensor nodes	n
Number of anchor nodes	a
Anchor nodes density	$A_d = (a/(n + a))$ %

to uncertain initial position of sensor nodes. Hence, its uncertainty is high until the Kalman filter receives more measurements and localization error will decrease dramatically as prediction and correction done then oscillates around small value because the Kalman gain (K_{gk}) reaches some balance[19]. As shown, the proposed scheme has a lower localization error than the two classes of FOKF algorithm because simulation time is long so FOKF algorithm doesn't have the measurement data for long time thus the estimation error increase[17].

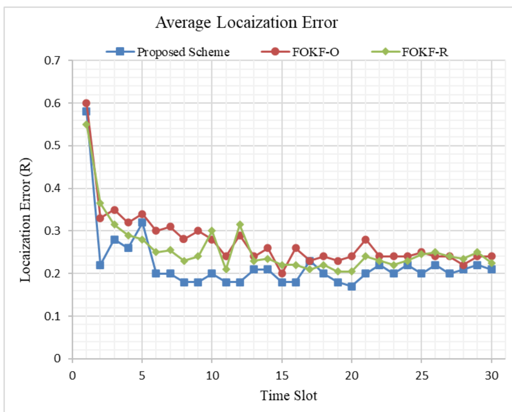

Fig 3. Localization Error Comparison

4.2 Impact of varying Anchor Node Density

As the number of anchor nodes increase, the localization error decreases because the measurements given to the Kalman filter become more accurate[20]. In this experiment, the total number of sensor and anchor nodes is 350 and anchor density varied from 1% to 15%. As shown in Figure 4, the proposed scheme has a lower localization error than the two classes of FOKF algorithm, which has very high localization error when anchor density is lower than 3%. However, the proposed scheme performs adequately even for a low anchor density because the Kalman filter makes a compromise between the predicted state and the measurements. Finally, the proposed scheme outperforms FOKF-O and FOKF-R algorithms when anchor density is 1% or above.

4.3 Impact of varying Moving Speed

In this experiment, number of sensor nodes kept at 322 and number of anchor nodes is 28 and the maximum speed V_{max} varies from 0.2R to 2R per slot time. According to the proposed scheme, the node speed affects the localization error in two ways. The increased speed makes the measured locations given by anchor nodes less accurate since the next possible locations fall into a larger region and the Kalman gain K_{gk} value decreased so, the Kalman filter will not depend closely on the measurements obtained. On the other hand, faster movement leads to more new anchor nodes in each time step, and the Kalman gain will be increased give the chance to depend on the measurements obtained from anchor nodes, hence more impossible locations can be filtered. As shown in Figure 5, as the moving speed increases, the localization error also increases that is because each sensor

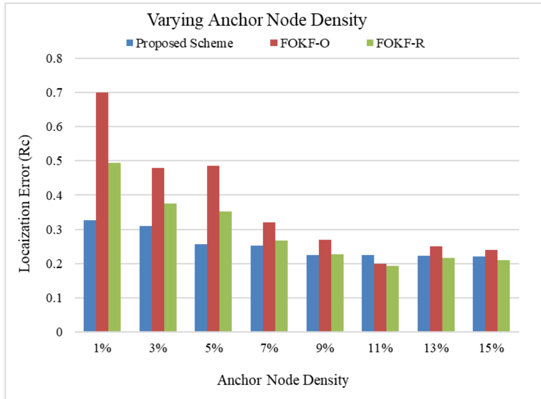

Fig 4. Impact of Varying Anchor Node Density

node lose its connection with anchor nodes in short time [21]. As shown, the proposed scheme has a lower localization error than FOKF-O and FOKF-R algorithms under different moving speeds.

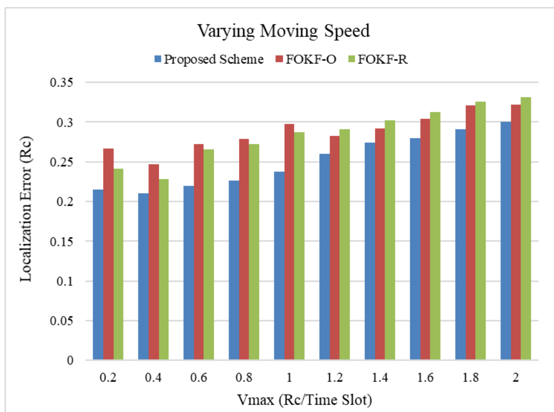

Fig 5. Impact of Varying Sensor Moving Speed

4.4 Effect of Radio Transmission Irregularity

Variability in actual radio transmission patterns can have a substantial impact on localization accuracy depending on the localization scheme. The degree of irregularity (DOI) is used to denote the maximum radio range variation in the direction of radio propagation, which is chosen randomly from [(1-DOI) x Rc, (1+DOI) x Rc]. For example, when DOI equals 0.2, the actual radio range in each direction randomly chosen from [0.8Rc, 1.2Rc]. In this experiment, the number of sensor nodes is settled at 322 and the number of anchor nodes at 28 and V_{max} = Rc/time slot. As illustrated in Figure 6, as DOI increases, the variance of the maximum transmission range under different direction increases and hence localization error increases [21]. Irrespective of increased localization error, the proposed scheme has a lower localization error than FOKF-O and FOKF-R algorithms when varying degree of irregularity.

4.5 Impact of Mobility Models

In the following, we will provide a comparative study between the proposed scheme, the FOKF-O and FOKF-R algorithms under different mobility models. According to the first slot shown in the following figures, the Kalman filter uncertain about the initial position of sensor node so it has high localization error initially. As time goes by, the Kalman filter will get accurate measurements which will be corrected according to the value of Kalman gain K_{gk} [22].

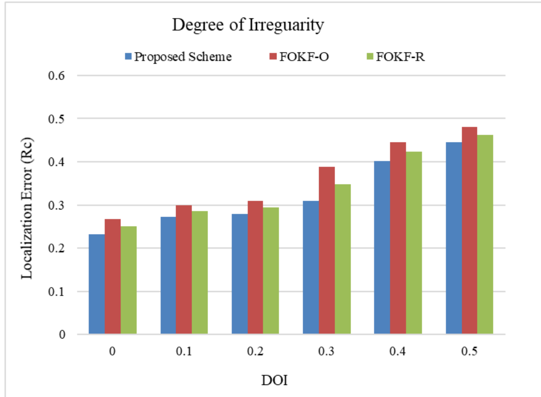

Fig 6. Effect of Degree of Irregularity

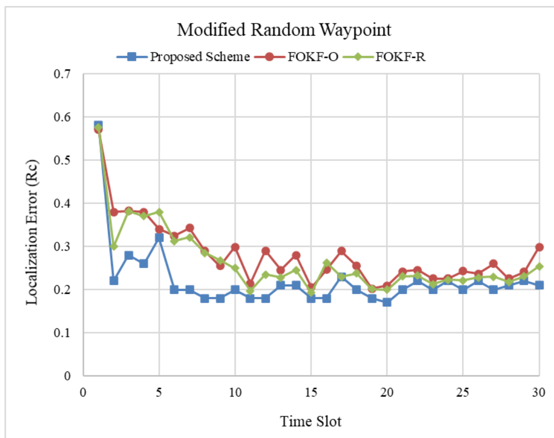

Fig 7. The Modified Random Waypoint Mobility Model

As show in Figure 7, Modified Random Waypoint mobility model has been used instead of regular Random Waypoint because it fails to provide a steady state in that the average speed consistently decreases over time[21], and therefore should not be directly used for simulation. As shown, the proposed scheme has a lower localization error than FOKF-O and FOKF-R algorithms over all slots of simulation time.

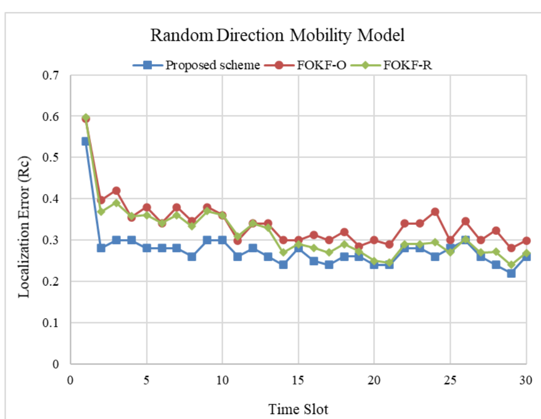

Fig 8. Random Direction Mobility Model

Random Direction mobility model is used in Figure 8, where sensor node chooses a heading direction at each time instance 1, 2, ..., k, and moves along that direction until the next time instance. The heading direction $\boldsymbol{\theta_i[k]}$ is uniformly distributed in $\mathbf{[0, 2\pi]}$, $\forall_{\,i,k}$. As shown in Figure 8, the proposed scheme has a lower localization error at different time slots [23].

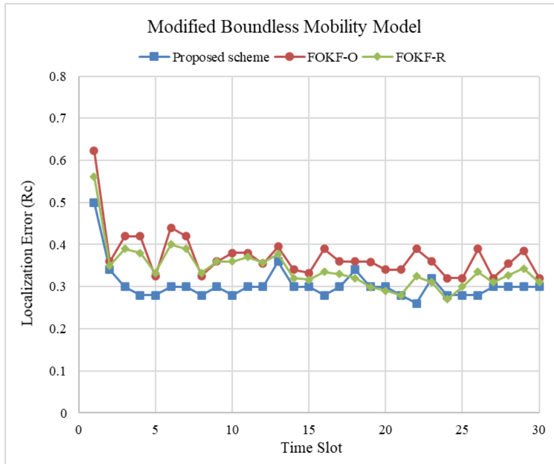

Fig 9. Modified Boundless Mobility Model

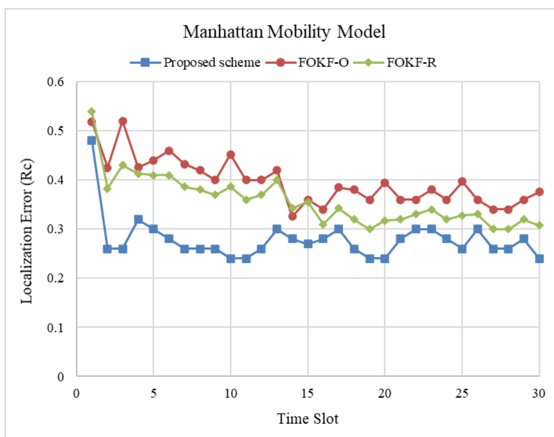

Fig 10. Manhattan Mobility Model

Figure 9 presents the impact of the Modified Boundless mobility model on the proposed scheme. The deployment area is being converted into a boundless area where a node goes off the deployment area from one side, it will appear from the other side with the same direction and speed [24]. As shown, at initial time both schemes have the same localization error at high value until the time slot 3, where the proposed scheme has a lower localization error than FOKF-O and FOKF-R algorithms. In Figure 10, Manhattan mobility model was studied to address the effect of the movement for sensor nodes in horizontal and vertical directions [24]. As shown the proposed scheme has a lower localization error than FOKF-O and FOKF-R algorithms during all simulation slots.

As shown in Figure 11, Reference Point Group Mobility (RPGM), each node belongs to a group where every node follows a logical center (group leader) that determines the group's motion behavior. The nodes in a group are usually randomly distributed around the reference point. The different nodes use their own mobility model and are then added to the reference point which drives them in the direction of the group. At each instant, every node has a speed and direction that is derived by randomly deviating from that of the group leader [24]. As shown, the proposed scheme has a lower localization error at most of time slots compared with FOKF-O and FOKF-R algorithms. The final mobility model used in this study is Freeway mobility model was used to study the effect of movement of mobile sensors which is restricted to its lane on the freeway [24]. From Figure 12, it can be stated that the proposed scheme has low localization error compared with the FOKF-O and FOKF-R algorithms.

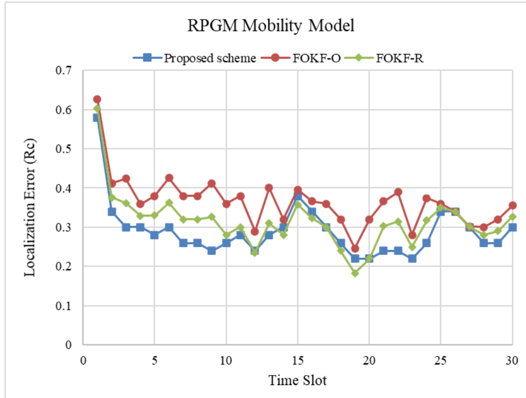

Fig 11. RPGM Mobility Model

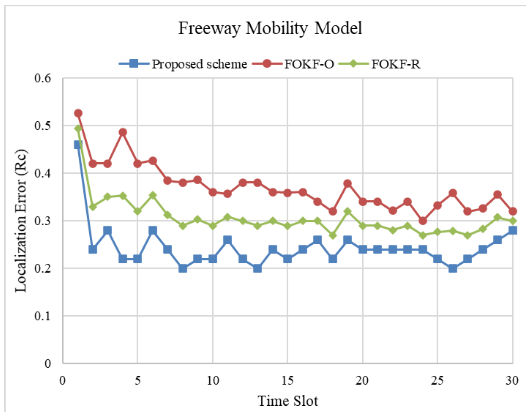

Fig 12. Freeway Mobility Model

4.6 Coverage

Coverage is defined as the percentage of localized sensor nodes according to the total number of sensor nodes in the deployment area. In this section, the impact of varying anchor nodes density on the total number of localized sensor nodes will be studied. As shown in Figure 13, as the percentage of anchor nodes increases, the percentage of localized sensor nodes also increases due to the increased possibility that sensor nodes receives more beacon messages from anchor nodes[25]. As shown, the proposed scheme has high coverage than FOKF-O and FOKF-R algorithms.

4.7 Communication Cost

Communication cost is defined as the total number of exchanged beacons between anchor and sensor nodes during localization process. In this experiment total number of nodes is 350 node (include both sensor and anchor nodes), with 322 sensor nodes and 28 anchor nodes. As shown in Figure 14, the proposed scheme has the lowest communication overhead because it needs only 1-hop and 2-hop anchor nodes participating in localization process. Communication cost has an impact on the power consumed[21], therefore the proposed scheme is suitable for wireless sensor networks because it has lower communication cost hence saves power and maximize network lifetime.

5 Conclusion

The Kalman filter is a robust technique which is capable of localizing using noisy measurements in a wireless sensor network. Thus, in this study, the Kalman filter technique has been applied to the information from anchor nodes to estimate the location of sensor nodes, and further improved the localization accuracy. A comparative study between the proposed scheme and the two

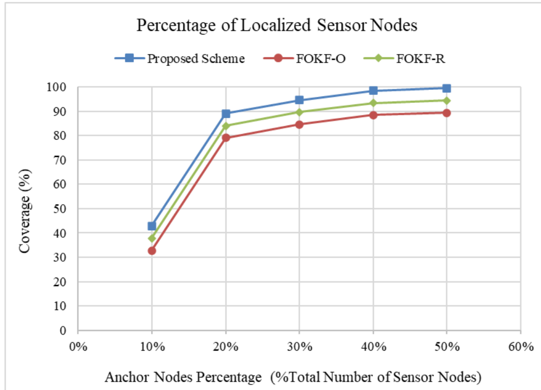

Fig 13. Coverage

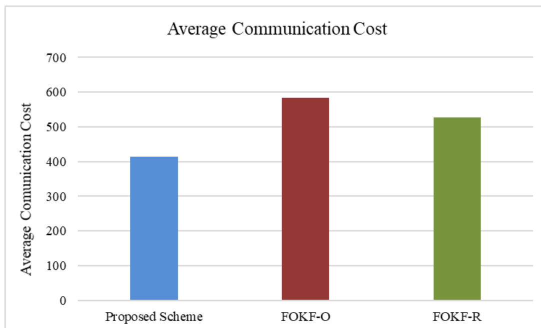

Fig 14. Communication Cost

classes of FOKF algorithm (FOKF-O and FOKF-R) under different and extensive simulations. Simulation results show that the proposed localization scheme outperforms FOKF algorithms in terms of localization accuracy, coverage and communication cost. The localization algorithms FOKF-O and FOKF-R are compared with each other based on their performance and also with the proposed localization scheme as shown in Table 3.

Table 3. Average Localization Error (%Rc) of the Proposed Scheme, FOKF-O and FOKF-R

Performance Metric	Proposed Scheme	FOKF-O	FOKF-R	Improved Percentage over	
				FOKF-O	FOKF-R
During Simulation Time	0.221	0.276	0.257	5%	4%
Anchor Nodes Density	0.255	0.368	0.292	11%	4%
Moving Speed	0.261	0.296	0.299	4%	4%
DOI	0.323	0.365	0.344	4%	2%
Modified Random Way-point	0.221	0.281	0.265	6%	4%
Random Direction	0.277	0.341	0.316	6%	4%
Modified Boundless	0.305	0.373	0.343	7%	4%
Manhattan	0.278	0.396	0.357	12%	8%
Freeway	0.244	0.370	0.307	13%	6%
RPGM	0.290	0.365	0.314	7%	2%

Simulation experiments reveal that the proposed scheme can provide accurate localization even when memory limits are severe, the anchor and/or sensor nodes density is low and network transmissions are highly irregular. The proposed scheme saves energy and increases network lifetime, hence it is a proper solution for many applications in Mobile Sensor Networks and is a suitable scheme to be implemented on the resource-limited sensor nodes.

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