Identification of the Optimum Relocalization Time in the Mobile Wireless Sensor Network using Time-Bounded Relocalization Methodology

Mona Nasseri, *Member, IEEE,* Junghwan Kim, *Senior Member, IEEE,* Robert Green, *Member, IEEE* and Mansoor Alam, *Senior Member, IEEE*

Abstract*—Contrary to the static sensor network which requires one-time localization, a mobile wireless sensor network (MWSN), requires estimation of the optimum time to retrigger the localization of the network, to accurately identify the sensor location after certain movements. However, triggering relocalization at pre-defined time intervals without proper consideration of the dynamic movement of sensors is insubstantial and results in poor resource management. In this paper, a new algorithm called time-bounded relocalization (TBR) is proposed to identify the optimum relocalization time for the entire MWSN using the time-bounded localization method based on the analysis of the sensors' mobility pattern. In the proposed algorithm, the optimum re-triggering time across the entire network can be calculated in two phases: Local and Global Relocalizations. In the first phase, an island-based clustering method is used to estimate the local relocalization time. Next, the estimated local times are then used to decide the optimum global relocalization time based on the statistical property of the estimated local times. For these calculations, a probabilistic model of the random waypoint (RWP) is selected. The soundness of the proposed algorithm is initially validated by deriving the probabilistic model of the optimum re-triggering time and its accuracy is checked by Cramer Rao Lower Bound (CRLB). The proposed algorithm is then extensively tested by computer simulation using practical network parameters including the number of nodes, the size of the network, and various sizes of islands depending on the sensor mobility, to yield the respective optimum relocalization time. The simulation results show that by using the identified optimum relocalization time, the location estimation error can be reduced by up to 32% for the RWP model as compared with the case of using fixed relocalization time.

***Index Terms*—MWSN (Mobile Wireless Sensor network), Relocalization, TBR (Time Bounded Relocalization), Random Waypoint (RWP) model, CRLB (Cramer Rao Lower Bound)**

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I. INTRODUCTION

THE multiple spatially scattered sensor nodes in wireless sensor network (WSN) cooperate to pass data toward monitoring certain environmental conditions [1, 2]. A Mobile Wireless Sensor Network (MWSN) is a WSN including mobile sensors. Although the introduction of sensor mobility in the network causes several challenges in the new areas of study such as energy consumption, connectivity and coverage, recent studies have shown the advantages of taking mobility into consideration [3], and found that mobile entities can actually help to resolve problems within static networks such as energy efficiency [3-5]. One of the main benefits of including mobility is tracking of moving objects such as vehicles [6-9] as well as collecting data from remote places. Data collection is more useful when position information is available. In [10-14] the conventional localization methods are described in detail. However, the aspect of node mobility and its pattern have not been considered. On the other hand, a vast research has been done on MWSN localization techniques considering various parameters that affect localization such as anchor mobility, sensor density and sensing range [9, 15-19]. For example, in [16] authors have shown how to guide the mobile's movement to gather a sufficient number of distance samples between node pairs for node localization and, in [9] the minimum number of mobile sensors that is required to maintain the resolution for target tracking in an MWSN is derived. In [19] authors proposed a method in which, when a mobile node moves across a specific area, the neighboring nodes compute the sequence of the node's movements and predict the target entrance to another area. Although the integration of sensor mobility in localization can provide advantages in exact localization, it also brings

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about the issue of repeatedly localizing the mobile nodes. Due to this nature, nodes must be continually relocalized in order to maintain a satisfactory estimate of their positions [20]. Additionally, this relocalization must happen frequently enough to maintain a certain threshold of accuracy-localization error. In [21] Monte Carlo Localization (MCL) was proposed. MCL method assumes that time is divided into discrete time units and node is relocalized in each time unit. A comparative simulation study in the performance of MCL was done in [22] for four mobility models that shows, localization performance is different when node moves with different mobility model. However in the mentioned localization methods the optimum time intervals to trigger the localization is not studied.

In this research to apply localization, a time efficient method, called time bounded localization is chosen [23], focused on localization within a given time-bound. In this method, sensor nodes are localized after a predefined number of k rounds of information flooding, followed by stopping of broadcasting signals. However, it is no longer adequate for a MWSN that needs more frequent relocalization to reflect the dynamics of the mobile sensors. In this paper, towards resolving the fundamental uncertainty of the relocalization time in the dynamic MWSN, a new algorithm is proposed to find the optimum time to trigger the time bounded localization algorithm by considering the impact of mobile nodes. In this algorithm, each island including multiple nodes, is allowed to determine the time (interval) to begin relocalization which is optimum due to considering mobility and area specification rather than choosing a fixed time interval. Towards this goal, random waypoint (RWP) [24] mobility model is selected and used for mathematical analysis and its applicability is checked. For the considered mobility pattern, the proposed relocalization algorithm can provide the optimum relocalization interval as well as the significant reduction in localization error. Additionally, the proposed algorithm is applied to two other random movement patterns (Levy walk and Brownian motion) to check the applicability of the algorithm for a variety of movement patterns.

The remainder of the paper is organized as follows: A brief review of the time bounded localization method along with the introduction of RWP mobility pattern, is given in Section II. Section III describes the proposed Time Bounded Relocalization (TBR) algorithm to identify the best moment to trigger the relocalization process in MWSN. The results of extensive computer simulations to support the validity of the proposed algorithm, are discussed in Section IV followed by the conclusion in Section V.

II. Mobility-based Localization in MWSN

In the practical localization techniques for MWSNs, it is supposed that there exists a subset of nodes, called anchors, which know their locations. Anchors and unlocalized nodes move randomly within the network where the minimum and maximum velocity of a node are bounded. Anchors and localized nodes periodically broadcast their locations. However, the exact time to broadcast is not considered seriously in literatures, even though it is an important factor to save energy consumption and combat with spoofing.

A. *The Initial Time Bounded Localization (TBL)*

To estimate the sensors' location in a wireless network (both static and mobile), the Time Bounded Localization (TBL) method is applied [23] in this research, where the concept of localization within a specific time-bound is commonly introduced. In this method, the localization process is performed in several rounds of information flooding, which is limited to a specific k value. During one round of information flooding, a node broadcasts and receives data from all neighbors. The number of communication rounds is used as a metric to determine the required time to localize the network. For a specific value of k, all sensors in a k-hops graph can be localized within k rounds of communications, but the anchors located at more than k-hops away cannot contribute to the localization of the specific node [23]. An upper bound for k can be calculated easily. Based on the worst case scenario to connect all nodes, if two specific nodes have the highest possible distance (such as the rectangle area diagonal), the number of hops to connect them can be considered as an upper bound for k that depends on the node's transmission range. The coordinates of particular nodes are determined through communications between neighboring nodes. They measure the distance between them and calculate their locations by using location estimation methods such as trilateration or multilateration [10]. After k-rounds of information flooding, the entire network may be globally localized through communications. Global localization is achieved through the use of anchor nodes that know their locations in global coordinate systems. When there exists a large enough number of anchors, the network can always be localized to any time bound. However, in practice, there can be only a small number of anchors due to the high cost of algorithm.

In this research, it is assumed that during the first round of communication the anchor nodes broadcast messages including their locations. Unlocalized nodes, which receive signals from at least three anchor nodes, can estimate their distances to the anchor nodes and use the three circle intersection formulas to estimate their locations. In the next communication round, new localized nodes will also broadcast their estimated locations to help the rest of unlocalized nodes. As shown in Fig. 1, U_1 is connected to A_1, A_2 and A_3. After the first round of information flooding, it can estimate its location. But, Given that U_2 is connected to two anchor nodes, U_2 should wait until it receives location information from U_1. When U_1 is localized, its status will be changed from 'unlocalized' to 'localized'. It means, for U_2, it takes more than one round to get localized.

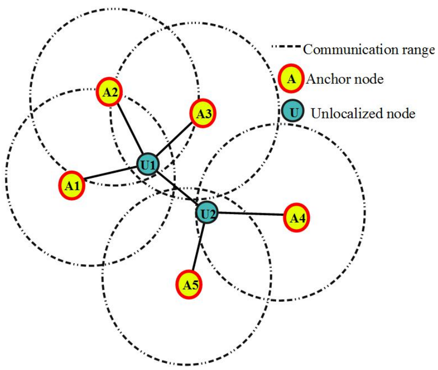


Fig. 1. Schematic of localization process

This process is repeated for the predefined k-rounds. After k-rounds the nodes stop sending signals, but some nodes still do not connect to at least three localized/anchor nodes. These nodes are referred to as isolated nodes and are not yet globally localized. In static environments, after determining an isolated island, fixed anchor nodes can be mounted in such places. Simulation of a random network in Contiki [25, 26] examines the relation between the number of anchor nodes and rounds. Fig. 2 shows that deploying more anchor nodes leads to a better result by increasing the number of localized nodes. In one round of information flooding, all nodes broadcast their information, including their node ID, localization status (localized or unlocalized), coordinates and a table including their distances to other nodes in their neighborhood. Each node that receives the signal from neighboring nodes in its transmission range can calculate its distance to them, which results in location estimation [10, 13, 27].

A 500m×500m random network, including 120 nodes, with a communication range of 60m is considered as an example. For the case when there are 20 to 50 anchor nodes, 4 rounds of information flooding are required to complete the relocalization process that results in successful localization for 26% to 51% of nodes. For 55- 65 anchor nodes, 5 rounds are needed to localize 76% to 93% of them. In this case, the maximum number of required rounds of communications to connect two nodes with the highest possible distance is 12 hops (i.e., diagonal/communication range). But after 5 rounds, no changes (in term of number of localized nodes) happen. Therefore, to save energy and time, nodes stop broadcasting to avoid eavesdropping.

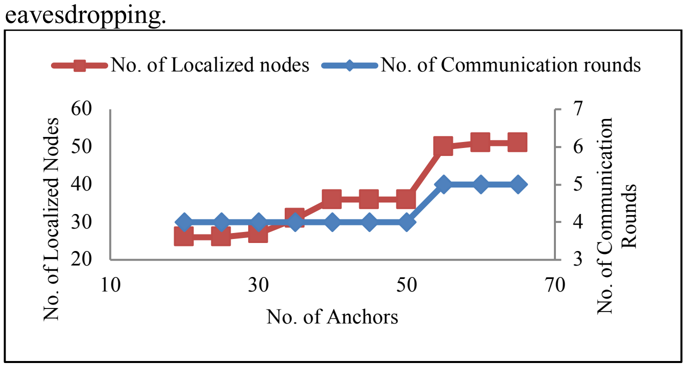


Fig. 2. Effects of number of anchor nodes on the number of localized nodes and the required information flooding rounds.

B. Relocalization in MWSN

However, to apply the TBL method to a MWSN, due to the relative movement of sensors, it is needed to relocalize in a given time bound and repeatedly update the localization information. One method is the relocalization of the entire network, either locally or globally, in the appropriate fixed time intervals. However, if relocalization takes place after extensive time periods, the accuracy of location estimation will be degraded. Inversely, if the same process is continuously repeated or performed in shorter time periods, higher costs (in terms of power consumption, calculation and message passing) will be imposed upon the system.

Since the major concern of this research in the MWSN is to identify the optimum time to trigger the relocalization after the successful initial localization, the statistical properties of the sensor mobility patterns must be investigated toward the development of the relocalization algorithm. For this, some of the most widely used mobility patterns are used to calculate the optimum retriggering time. Based on the analysis, a generalized time bounded relocalization (TBR) algorithm is proposed to estimate relocalization triggering time while it can provide minimum localization error.

C. Analysis of Node Movement Patterns

In a mobile WSN, the localization should repeatedly take place to reflect the nodes' movements. In such circumstances, the actual movement pattern of each node significantly affects the localization results.

Each sensor can move independently (i.e. entity mobility models) or according to another node's movement [24, 28-32]. The mobility patterns should show the information on movements of real sensor nodes, including the speed and movement direction during specific time intervals. Since moving in a specific manner or a straight line does not provide a comprehensive information of sensor nodes to deploy in a practical network, some widely suggested [24, 28, 31] random movement patterns, are investigated to test the proposed algorithm.

The most popular mobility model to assess mobile-ad-hoc network routing protocols is the random waypoint pattern (RWP) [24] due to its simplicity and availability. RWP is a synthetic model which has several parameters that can be adjusted to match with a particular scenario, including mobile wireless network and the location of an arbitrary packet in multi-hop network [24, 28]. In RWP specifications, nodes move along a zigzag path, containing straight legs between two waypoints. A node randomly chooses a destination point ('waypoint') in the area and moves with constant speed in a straight line to this point. After waiting a certain pause time, it chooses a new destination and speed, and moves with constant speed to the destination. The movement of a node from a starting position to its next destination is denoted as one movement period or transition. Fig. 3 shows the possible movement of a node in a RWP model such that nodes move from waypoint P_i to waypoint P_{i+1} with velocity v_i chosen from a random distribution $f_V(v)$ within [v_{min}, v_{max}]. Each node pauses at each waypoint, P_i, before moving to the next waypoint.

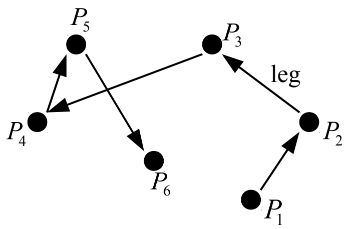


Fig. 3. Random waypoint movement pattern.

As mentioned earlier, relocalization in a MWSN should be triggered continuously at specific times. For a known movement pattern, to estimate the moment to trigger relocalization, probability density function (pdf) of node's movement can be exploited. To find the probability of the node's position moving according RWP, it is assumed that in a one dimensional space, random points are uniformly distributed on a line segment [0, a], hence the pdf of a node's location (f_{px}) is:

$$f_{P_x}(x) = \frac{1}{a} \quad for\ 0 < x < a \tag{1}$$

The probability that node moves from point x_1 to x_2, with the distance of $L \leq$ l, in the x_1-x_2 space is [33]:

$$P(L \leq l) = \iint f_{X_1 X_2}(x_1, x_2) dx_2 dx_1 = \iint f_{X_1}(x_1) f_{X_2}(x_2) dx_2 dx_1 \tag{2}$$

For specific distance limitations ($0<l<a$), the probability of (2) and its pdf are respectively defined as [33]:

$$\begin{aligned} &P(L \leq l) = \\ &\frac{1}{a^2}\left(\int_0^l \int_0^{x_1+l} dx_2 dx_1 + \int_l^{a-l} \int_{x_1-l}^{x_1+l} dx_2 dx_1 + \int_{a-l}^{a} \int_{x_1-l}^{a} dx_2 dx_1\right) = -\frac{1}{a^2} l^2 + \frac{2}{a} l, \\ &for\ 0 \leq l \leq a,\ L = \left|P_{x_1} - P_{x_2}\right| \\ &f_L(l) = \frac{\partial}{\partial l} P(L \leq l) = -\frac{2}{a^2} l + \frac{2}{a} \end{aligned} \tag{3}$$

In a rectangular area of size $a \times b$, the spatial distribution of two dimensional waypoint (P=(P_x, P_y)) is given by a uniform distribution [33]:

$$f_{P_x P_y}(x, y) = \begin{cases} \frac{1}{ab} & for\ 0 \leq x \leq a\ and\ 0 \leq y \leq b \\ 0 & else \end{cases} \tag{4}$$

Where distance between two waypoints P_1(P_{x1}, P_{y1}) and P_2(P_{x2}, P_{y2}) is defined as:

$$L = \sqrt{(P_{x1} - P_{x2})^2 + (P_{y1} - P_{y2})^2} = \sqrt{L_x^2 + L_y^2} \tag{5}$$

Since, random distances, L_x and L_y are independent, the joint pdf is given by [33]:

$$\begin{aligned} &f_{L_x L_y}(l_x, l_y) = f_L(l_x) f_L(l_y) = \\ &\frac{4}{a^2 b^2}(-l_x + a)(-l_y + b),\ for\ 0 \leq l_x \leq a,\ 0 \leq l_y \leq b \end{aligned} \tag{6}$$

The CDF can be found by the integration of (6) over the circle area $l_x^2 + l_y^2 \leq l$ [33].

$$P(L \leq l) = \begin{cases} \int_0^l \int_0^{\sqrt{l^2 - l_x^2}} f(l_x, l_y) dl_y dl_x,\ 0 \leq l \leq b \\ \int_0^b \int_0^{\sqrt{l^2 - b^2}} f(l_x, l_y) dl_y dl_x + \int_0^{\sqrt{l^2 - l_x^2}} \int_{\sqrt{l^2 - b^2}}^{l} f(l_x, l_y) dl_y dl_x\ \ b < l < a \\ \int_0^b \int_0^{\sqrt{l^2 - b^2}} f(l_x, l_y) dl_y dl_x + \int_0^{\sqrt{l^2 - l_x^2}} \int_{\sqrt{l^2 - b^2}}^{a} f(l_x, l_y) dl_y dl_x\ \ a \leq l \leq \sqrt{a^2 + b^2} \end{cases} \tag{7}$$

Solving these integrals by taking the derivative with respect to l and performing trigonometric simplifications ~~leads~~ to the following pdf of transition length L of nodes moving according to the RWP model in a rectangular area of size $a \times b$, where $a \geq b$, [33, 34]:

$$f_L(l) = \frac{4l}{a^2 b^2} . f_0(l), \quad where$$

$$f_0(l) = \begin{cases} \frac{\pi}{2} ab - al - bl + \frac{1}{2} l^2\ \ 0 \leq l \leq b \\ ab\ \arcsin\frac{b}{l} + a\sqrt{l^2 - b^2} - \frac{1}{2} b^2 - al\ \ b < l < a \\ ab\ \arcsin\frac{b}{l} + a\sqrt{l^2 - b^2} - \frac{1}{2} b^2 - ab\ \arccos\frac{a}{l} + \\ b\sqrt{l^2 - a^2} - \frac{1}{2} a^2 - \frac{1}{2} l^2\ \ a \leq l \leq \sqrt{a^2 + b^2} \end{cases} \tag{8}$$

In turn, to estimate the triggering moment, it is needed to calculate the transition time T which is the time of a node's transition from one waypoint to the next by moving distance L. According to RWP specifications mentioned earlier, it is assumed that the velocity is constant during one transition and is randomly chosen from a distribution, $f_V(v)$. Therefore the random variable T is given by,

$$T = \frac{L}{V} \quad where, \quad v_{\min} \leq v \leq v_{\max}, \quad v_{\min} > 0 \tag{9}$$

Assuming T is a random variable expressed as a function of transition length (L) and velocity (V):

$$g(l, v) = \frac{l}{v} \tag{10}$$

Since at each waypoint the node picks a new destination randomly and moves toward it at a constant random velocity, variables L and V are independent [29, 33] and the joint pdf can be represented as:

$$f_{LV}(l, v) = f_L(l) f_V(v) \tag{11}$$

Then pdf of transition time T is calculated by:

$$\begin{aligned} &E[T] = \int t f_T(t) dt = \int \int_{v_{\min}}^{v_{\max}} f_L(l) f_V(v) \frac{l}{v} dv dl = \\ &\int \int_{v_{\min}}^{v_{\max}} f_L(vt) f_V(v) \frac{vt}{v} v dv dt \\ &\int t f_T(t) dt = \int \int_{v_{\min}}^{v_{\max}} v f_L(vt) f_V(v) t dv dt \\ &f_T(t) = \int_{v_{\min}}^{v_{\max}} v f_L(vt) f_V(v) dv, \quad for\ 0 \leq t \leq t_{\max} = \frac{l_{\max}}{v_{\min}} \end{aligned} \tag{12}$$

Alternatively, E[T] can also be calculated in the term of E[L]:

$$E[T] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{l}{v} f_L(l) f_V(v) dl dv = E[L] \int_{v_{\min}}^{v_{\max}} \frac{1}{v} f_V(v) dv \tag{13}$$

For a square area $a \times a$, $f_T(t)$ for $l \leq a$ is calculated using (8) and (12):

$$f_L(vt) = \frac{4vt(\frac{1}{2}\pi a^2 - 2avt + \frac{1}{2}v^2t^2)}{a^4},\ f_V(v) = \frac{1}{v}\ \ for\ 0 \le l \le a$$
$$f_T(t) = \int_{v_{\min}}^{v_{\max}} f_L(vt)dv$$
$$f_T(t) = \frac{1}{2}\frac{t^3(v_{\max}^4 - v_{\min}^4)}{a^4} - \frac{8}{3}\frac{t^2(v_{\max}^3 - v_{\min}^3)}{a^3} + \frac{t\pi(v_{\max}^2 - v_{\min}^2)}{a^2}$$
(14)

To check the validity of the pdf $f_T(t)$ in (14), it should be determined that pdf has a positive value in the time domain and its total probability should be one. To simplify the calculation, (14) can be simplified as:

$$\alpha = \frac{(v_{\max}^4 - v_{\min}^4)}{a^4}, \beta = \frac{(v_{\max}^3 - v_{\min}^3)}{a^3}, \gamma = \frac{(v_{\max}^2 - v_{\min}^2)}{a^2} \tag{15}$$

By the result,

$$f_T(t) = \frac{1}{2}\alpha t - \frac{8}{3}\beta t^2 + \pi\gamma t$$
$$where, \tag{16}$$
$$0 < t \le \frac{8\beta - 3\sqrt{(\frac{64\beta^2}{9} - 2\pi\alpha\gamma)}}{3\alpha}$$

Then corresponding mean and variance of transition time T will be:

$$\begin{aligned}
&E[T] = \mu = 0.1\alpha t^5 - 0.6\beta t^4 + 1.046\gamma t^3 \\
&E[(T-\mu)^2] = \sigma^2 = 0.00035\alpha^3 t^{14} - 0.0071\beta\alpha^2 t^{13} + \\
&0.83t^{12}(0.5\alpha\lambda + 0.35\beta^3\alpha + \pi\alpha^2\gamma 10^{-2}) + \\
&0.09t^{11}(-1.11\gamma\beta\alpha - 2.6\beta\lambda + \\
&0.1t^{10}(0.5\alpha\omega + 3.72\gamma\beta^2 + \pi\gamma\lambda)0.11t^9(0.66\beta\alpha - 2.66\beta\omega - 4.38\gamma^2\beta) + \\
&0.125t^8(-1.04\gamma\alpha - 3.5\beta^2 + \pi\alpha\omega) + 1.39\gamma\beta t^7 + \\
&0.16t^6(0.5\alpha - 6.57\gamma^2) - 0.53\beta t^5 + 0.78\gamma t^4 \\
&where, \\
&\qquad \lambda = 0.209\gamma\alpha + 0.44\beta^2 \quad and \quad \omega = -0.2\alpha + 1.09\gamma^2
\end{aligned} \tag{17}$$

Since the integral of pdf over time duration should be equal to one, v_{min} is assumed to be square root of v_{max} to meet this condition. For the special case of maximum velocity of 25 m/s in a 500m×500m area, pdf of (16) is valid in the time domain of (0, 33sec] which is shown in Fig. 4 compared to approximated Gaussian pdf which will be discussed later. Mean and standard deviation of (17) for time duration (0, 33] are 16.65sec and 10.2, respectively.

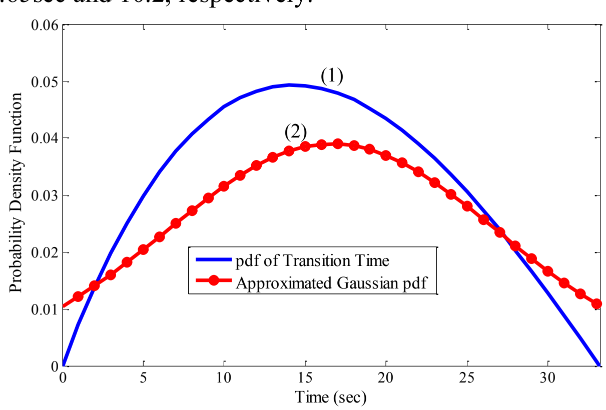


Fig. 4. Probability density function of transition time (curve 1) and the approximated Gaussian pdf (curve 2) for 500m×500m area with maximum velocity of 25 m/s

D. Triggering Time for Relocalization: Case of RWP Model

Relocalization should be triggered at the time close to the moment at which a node reaches the next waypoint. Before a node transits to the next waypoint, it moves in the same direction with the constant velocity based on the RWP model. At the waypoint, the velocity is changed and the node moves in a new direction, which necessitates new relocalization. To find the pdf of relocalization triggering time, it is needed to use the pdf of the transition time. Based on the obtained pdf of (16), it can be approximated as a Gaussian pdf of (18), where t_r denotes the random value of the re-triggering time.

$$f_{T_r}(t_r) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(t_r-\mu)^2}{2\sigma^2}} \tag{18}$$

In case of 500m×500m area with a maximum speed of 25m/sec, the mean and variance of pdf shown in Fig. 4 is used to approximate the corresponding Gaussian pdf of the local relocalization triggering time using (18).

E. Cramer Rao Lower Bound (CRLB) of the relocalization triggering time-Case of RWP Model

The pdf is used to estimate the local relocalization triggering time. To check the quality of the triggering time estimator, the Cramer Rao Lower Bound (CRLB) [35, 36] can be used. CRLB on the accuracy of the statistics is obtained by deriving the Fisher Information from a partial derivative of the approximated pdf of the relocalization triggering time. Using the RWP model, it is considered that the triggering times are n random samples $T_1;\dots;T_n$ from a distribution whose pdf is $f(t;\theta)$, where θ is an unknown variable. The fisher information is used to determine the lower bound of the variance of an estimator of the parameter θ. Assume that $\hat{\theta}$ be an arbitrary estimator of θ which is a function of triggering time, with $E_\theta(\hat{\theta})=m(\theta)$, and finite variance. For the independent random variables $T_1;\dots;T_n$ defined as (19),

$$l_n(t;\theta) = \log f_n(t;\theta) = \sum_{i=1}^{n}\log f(t_i;\theta) = \sum_{i=1}^{n} l(t_i;\theta) \tag{19}$$

And l', the derivative of $l_n(t;\theta)$, is found as: $l_n'(t;\theta)=f_n'(t;\theta)/f_n(t;\theta)$. The corresponding Fisher information $I_n(\theta)$ is shown as:

$$I_n(\theta) = E[(l_n'(t;\theta))^2] = \int\dots\int (l_n'(t;\theta))^2 f_n(t;\theta)dt_1\dots dt_n \tag{20}$$

The covariance between $\hat{\theta}$ and $l'(t;\theta)$ is derived by considering Leibniz's rule to calculate $E[l'(t;\theta)]$:

$$E_\theta[l'(t;\theta)] = \int l'(t;\theta)f(t;\theta)dt = \int \frac{f'(t;\theta)}{f(t;\theta)}f(t;\theta)dt =$$
$$\int f'(t;\theta)dt = \frac{\partial}{\partial\theta}\int f(t;\theta)dt = 0$$

Therefore,

$$Cov_\theta[\hat{\theta}, l'(t;\theta)] = \frac{\partial}{\partial\theta}E_\theta[\hat{\theta}] = m'(\theta) \tag{21}$$

By using the Cauchy-Schwartz inequality and the definition of $I_n(\theta)$,

$$\{Cov_{\theta}[\hat{\theta}, l_n'(t;\theta)]\}^2 = [m'(\theta)]^2 \leq \sigma_{\hat{\theta}}^2 I_n(\theta) = nI(\theta)\sigma_{\hat{\theta}}^2 \quad (22)$$

The lower bound of variance of the estimator $\hat{\theta}$ or Cramer-Rao inequality is

$$\sigma_{\hat{\theta}}^2 \geq \frac{[m'(\theta)]^2}{nI(\theta)} \quad (23)$$

If the information $I(\theta)$ increases, the variance of estimator decreases, which leads to the enhancement of the quality of the estimator. For an unbiased estimator, it can be claimed that:

$$m(\theta) = E_{\theta}(\hat{\theta}) = \theta, \;\; m'(\theta) = \frac{d}{d\theta} m(\theta) = 1 \quad (24)$$

Therefore:

$$\sigma_{\hat{\theta}}^2 \geq \frac{1}{nI(\theta)} \quad (25)$$

The right-hand side of (25) is called the Cramer-Rao Lower Bound (CRLB), and under certain conditions, no other unbiased estimator of the parameter θ based on an i.i.d. samples of size n can have a variance smaller than CRLB. The CRLB of the pdf defined in (18) for calculated mean and variance for a 500m×500m area, including n=100 node sample case, is shown in Fig. 5. The minimum value of CRLB is 1.5 when the local retriggering t_r is around 33 sec. For t_r greater than 33 sec, it starts to increase rapidly because node reaches to the next waypoint and changes its direction. Since in this case the CRLB depends on the velocity and size of the area, it will vary for different size of area. As is demonstrated in Fig. 5, CRLB is calculated for different area dimensions, assuming the identical node density (0.0004) and the same maximum velocity (25 m/s). In all cases the minimum value of CRLB corresponds to the time at which a node in the island has a high probability to change its movement direction. In other words, CRLB can be effectively used to identify the time to trigger relocalization locally.

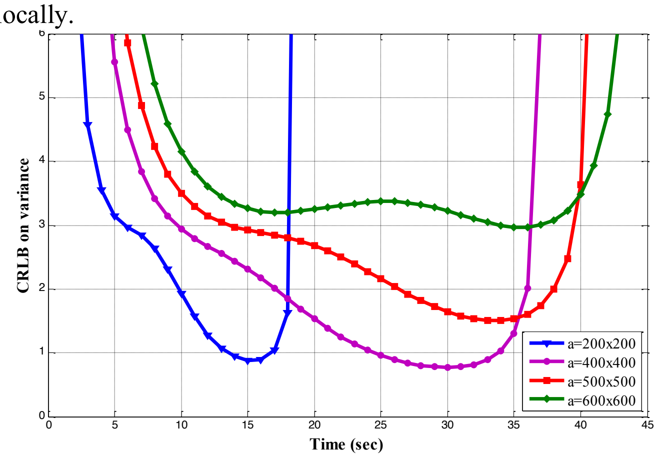


Fig. 5. CRLB on the variance of estimated local relocalization time for different sizes of the area

III. The Proposed Time Bounded Relocalization (TBR) Algorithm

In this section, an algorithm is proposed to calculate the optimum time to trigger relocalization. The proposed algorithm is also validated using the results of mathematical analyses of movement patterns given in Section II.

The proposed TBR algorithm consists of a two-step relocalization procedure for the enhanced resource management. In the conventional localization, after the initial localization, each node knows its own position as well as its neighbor's within their communication range. In principle, the relocalization can be done at every pre-determined fixed time interval for the whole area. If the speed of mobile nodes is different, it is beneficial to do the relocalization at different times for different mobile nodes. However, it is complicated and time-consuming to perform the individual relocalization. Hence, it would be more advantageous to divide the network to several islands (or clusters) and relocalize each island at a specific time depending on the average speed of multiple nodes belonging to the respective island. This process is called as the Step.1: Local Relocalization. To achieve this, it is needed to identify the maximum average node speed in each isolated island. Upon completion of Step 1, Global Relocalization can be performed as Step 2. Eventually the global relocalizing time (T_{global}), that properly reflects the variation of island-based local relocalization time T_{local} (obtained in Step 1) due to node mobility and the characteristics of the different clusters, can be optimized.

A. Method of Clustering

Toward local relocalization (of Step 1), method of clustering matters. To determine islands, Monte-Carlo computation is used to repeatedly check if a node still belongs to a cluster. In the localization process, results of nodes' communications can provide information on the nodes and their neighbors, with the distances smaller than R (communication range). In the clustering method used in this paper, a node is randomly selected and considered as a core node which is connected to several nodes in its communication range, via edges. The end node of the edge is also connected to other nodes. The path is followed until reaching a node which terminates the path. For example, in Fig. 6, node e is connected to d and h in the first hop, and node d is connected to b and g. Nodes h, b and g are terminated nodes. All paths that start from e should be followed until reaching the terminated nodes and all nodes that are passed are considered as a cluster. Then, another node like f is selected as a core node and the same process is repeated.

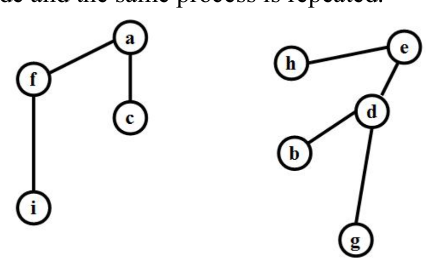


Fig. 6. Clustering process

In the programming process, all information from M nodes is collected in an M×M matrix (here H). For connected nodes i and j, the corresponding matrix element (m_{ij}) should be one, otherwise zero. It is supposed that k elements in row i are equal to one which shows k the first hop connected nodes to i. k

corresponding rows are checked to find the second hop connected nodes to *i*. This process continues until all nodes that are connected are picked and considered as a cluster. Then all the rows and columns that relate to cluster members, will be removed from '*H*' and a smaller matrix would be obtained. In several steps, nodes and their linked nodes can be removed from matrix '*H*', to form an island (I_n). This process would be repeated several times to distinguish all *N* clusters to consider them as islands. The process is depicted in Fig. 7.

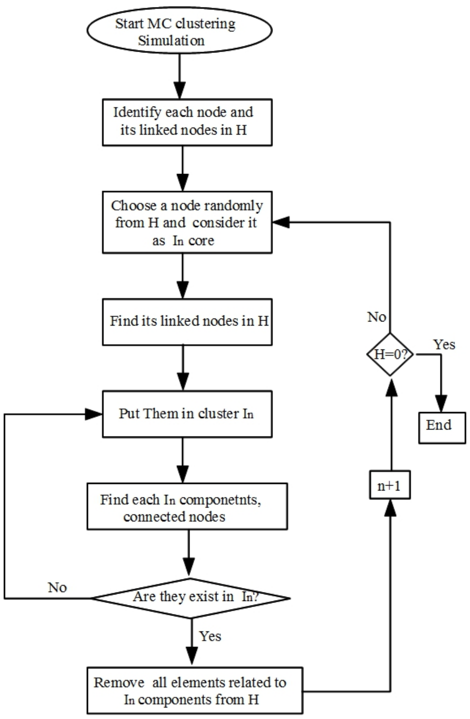


Fig. 7. Monte-Carlo process-based Clustering method

After identifying islands, it is time to estimate relocalization triggering time in two steps, which are explained as follows:

Step 1-Local Relocalization

To identify the proper time for triggering Local Relocalization, "border or maximum distance travel (*D*)" and "the maximum average velocity of nodes in an island (*v*)" are included. Each island is relocalized at a time 'T_{local}' that is estimated from the velocity of island members (nodes) and dimension factors of the area. $T_{local1}, \ldots, T_{localN}$ are defined for *N* recognizable islands/clusters, including the minimum and maximum values as T_{min} and T_{max}.

To find the maximum distance '*D*' that a sensor node can travel, two methods are used in this research depending on the randomness of the node movement. In the first method, it is assumed that a node can move as far as the dimension of the area in a time gap between two relocalization processes, which is appropriate for indoors. In the second method called "Connection Loss (CL)", the case is considered when mobile node loses the connection and exits the area of an island. To calculate it mathematically, the distance of the farthest node that connected to the mobile node in the island is found (call it *P*):

$$P = \max(d_{i,1}, d_{i,2}, \ldots, d_{i,m}),$$
$$m = \textit{no. of connected nodes to node } i,\ d_{i,k} \le R \tag{26}$$

Where $d_{i,k}$ is the distance between mobile node *i* and neighboring node *k*. Then a circle around the mobile node with radius *P* is considered. Points on the circle are shown by (x_c, y_c) and the number of them depends on the selected '*n*' in (27) that determines the degree of precision of the estimator. Fig. 8 shows an arbitrary point on the circular area.

$$x_d(\theta) = P \times \cos(\theta), \qquad x_c(\theta) = x_d(\theta) + x_P, \theta \in (0 : \frac{1}{n} : 2\pi)$$
$$y_d(\theta) = P \times \sin(\theta), \qquad y_c(\theta) = y_d(\theta) + y_P \tag{27}$$

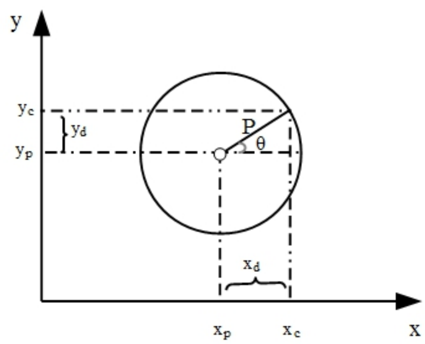


Fig. 8. Finding the distance *P*, using Connection Loss method

Where (x_P, y_P) is the coordinate of the selected farthest node. Next, it is needed to check if the mobile node in the circle area still belongs to the specific island (it should be checked for the different points at circle border). If it loses the connection, *P* is considered as *D* to estimate the relocalization time. Otherwise, the radius *P* can be changed by a small incremental step. This process should be done for all mobile nodes to calculate the time *T* that is needed for a node to go to distance *D* with speed *v*. The drawback of the CL method is that, each node should be checked online to recognize the moment of losing the connection. But in the first method, it is applicable to use the available movement history of a node to determine *D* and *v*.

Moreover, we need the speed information of the nodes. Nodes can approximate their velocity using different methods such as measuring RF Doppler shift of the broadcasted beacon [37]. In the simulation part, a random velocity is chosen for node which is between minimum and maximum velocities. Therefore, during a predefined time interval for global relocalizing, each island will be relocalized in a time T_{local} (T=D/V) estimated by velocity and dimension of the area using (28).

$$T_{local} = f(v, d) \quad \textit{where} \quad v = \max(v_1, v_2, \ldots, v_j)$$
$$\textit{and} \quad v_k = \frac{1}{n}\sum_{s=1}^{n} v_s \tag{28}$$

Where *v* is the maximum mean speed of mobile nodes in an island, and *j* denotes the number of mobile nodes in a given island. To find v_k, the mean speed of each sensor node in its island, the average value of speed is calculated within last available *T* seconds movement history of the specific node that includes ‘*n*’ times changes in speed.

Step 2-Global Relocalization

It is assumed that the predefined time interval, T_{fix}, is defined as the time to trigger relocalization globally before applying the proposed algorithm. T_{fix} can be chosen as $2t_{max}$, according to the maximum transition time in (12), if the maximum transition length and the minimum velocity of a node are known. In Step 2, global relocalization time (T_{fix}) is adjusted based on the results of Step 1 ($T_{local1},\ldots, T_{localN}$). The obtained T_{local} values show each island should be periodically localized after T_{local} seconds. Thus, a global relocalization time should be beneficial for all islands, while considering the main island as our priority, because it includes the majority of mobile nodes. Additionally, in a mobile network, its topology is changing. So, the clustering should be carried out repeatedly, and new T_{local} values is obtained at each running of the relocalization algorithm. In the following simulation section, the performance of the algorithm will be tested for several time intervals to check the validity of the proposed algorithm. However, there are some factors that affect the performance of the algorithm with respect to the identification of global relocalization time (T_{global}), based on the distribution of T_{local} values obtained from Step 1 using clustering method:

If the standard deviation of $T_{local1},\ldots, T_{localN}$ is small and $T_{min}\leq T_{local1}, T_{local2},\ldots, T_{localN}\leq T_{max}$, then the time for global relocalization (T_{global}) could be a maximum of twice the T_{min} to reduce the localization error, but it must be larger than T_{max}, such that:

$$T_{global} = 2T_{\min} > T_{\max} \tag{29}$$

If the standard deviation of $T_{local1},\ldots, T_{localN}$ is large, which shows the higher unpredictability on the moving distances of the mobile nodes, the twice the median of obtained T_{local}s ($T_{local1},\ldots, T_{localN}$) is appropriate as T_{global} such that,

$$T_{global} = 2T_{med} \geq T_{\max} \tag{30}$$

Hence, some islands with large T_{local} which is comparable to $2T_{med}$, should be relocalized once after $2T_{med}$ (sec), while islands with a smaller T_{local} are localized two times. In other words, some nodes need to be relocalized after a longer time gap. In both cases, T_{global} is compared with T_{fix}, which is mentioned in Function 3 in Algorithm I.

The relocalization process reflecting the above discussion is shown in Algorithm I and will be used to obtain the global relocalization time. In the proposed algorithm, the maximum velocity of a node is assumed to be known and the average speed of each node, v_{avg} is used to calculate the travel distance during T_{local}. It is also assumed that there are I islands with J mobile nodes in the island.

ALGORITHM I
RELOCALIZATION TIME ESTIMATION

```
Function 1
  Move mobile nodes

Main function
  For i=1:I
    For j=1:J

     Estimate the average velocity of the nodes at
each island
     Calculate the average node velocity if it is
not directly available (Vji)

    End
        Select and save the highest average
velocity
        Find the further distance that mobile node
        can go (D)
        Find the needed time to travel to D (Tlocal)
  End

Function 2
Trigger the local localization for each Island in
calculated time (Tlocal)

Function 3
Find Tglobal
  If Tglobal <Tfix
    Trigger the global localization in Tglobal
  Else
    Trigger the localization at Tfix
```

According to the Algorithm I, each island is localized at a time T_{local} and the whole network can be globally localized at predefined time T_{fix} or T_{global}. On the other hand, for networks with high node density, all nodes can be connected, which leads to having just one island, resulting in one value for T_{local} at which the whole network will be relocalized globally. To be consistent in using proposed method of Algorithm I, in a network including whole nodes connected, T_{local} and T_{global} will be reported separately, so that T_{global} is twice T_{local}. The same process will be repeated after completion of algorithm. The local relocalization will be triggered after T_{local}. The complete proposed relocalization process is shown in the flowchart of Fig. 9. Note that the value $T_{current}$ refers to the current time during simulation and T_{k-1} denotes the estimated time to trigger relocalization at the most recent relocalization run (k indicates the relocalization round number).

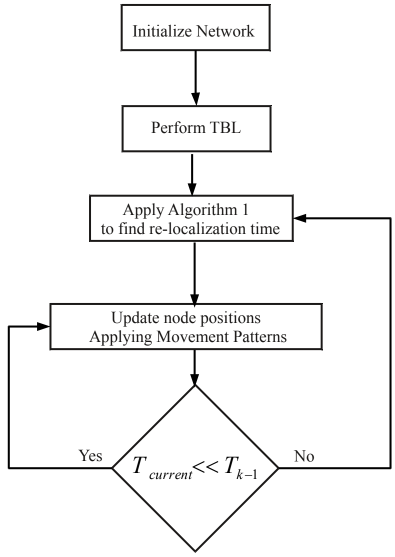


Fig. 9. A flowchart of proposed process to trigger relocalization for several time intervals

IV. Network Simulation using The Proposed TBR Algorithm

A. *Test of TBR algorithm with Random Network Topology*

Matlab based computer simulation is used to test the proposed time bounded relocalization algorithm. To properly reflect the characteristics of different clusters that do not share any common nodes, a network model with randomly distributed nodes is considered. To find the appropriate local relocalization time T_{local}, the number of nodes is initially varied in the fixed network size of 500m×500m and the relocalization triggering time, T_{global}, is calculated based on Algorithm I (assuming the communication range of 60 meters, minimum and maximum velocity of 5 and 25m/s respectively). In Table I, while the total number of nodes is increased from 50 to 500, it is assumed that 50 % of them are mobile to properly reflect the effect of node mobility. Moreover, to examine the effect of the proposed algorithm, any islands (not isolated one) including mobile nodes more than 5% of the total mobile nodes in a network are regarded as a considerable island to ensure that at least one mobile node exists in an island. Simulations are run 10 times per each node size and the average values of T_{local} are reported. Note that for a network with more than 150 nodes, the number of islands turns out to be one, which means that all the nodes are connected because they get closer. Since the maximum and minimum velocity as well as the size of the area are all fixed, there is only a small change among reported minimum average local relocalization times. As is shown in Table I, when the number of nodes is 50 and 100 (smaller than 150), multiple islands exist in the network and the average values of T_{local}s are reported. However, when the number of nodes gets larger (more than 150), the calculated T_{local}s, are almost identical, resulting negligible standard deviation due to the fact that all the nodes are connected and there exist just one island.

Table I Local Relocalization time T_{local} for 50-500 nodes, including 50% mobile nodes

No. of nodes	No. of islands	Considerable islands, including more than 5% mobile nodes	Average local Relocalization time among main islands
50	6	3	33.66
100	3	2	31.35
150	1	-	29.77
200	1	-	28.49
250	1	-	28.94
300	1	-	27.85
350	1	-	28.54
400	1	-	27.68
450	1	-	27.14
500	1	-	27.89

Next, the number of nodes is assumed constant (120 nodes), but the size of the area varies while the overall density of the mobile node is still fixed as 50%. A random-topology network is shown in Fig. 10(a) for a 400m×400m area. Table II shows the results of T_{local} after the clustering assuming the communication range of 60m. By increasing the size of the network, the density of nodes decreases because the total number of nodes is fixed. To calculate the relocalization time, the islands that include more than 5% of mobile nodes are considered. For smaller areas such as 400m×400m (Fig. 10 (b)), all the nodes are connected within one main island. By increasing the size, it is observed that the number of islands increases naturally to cover a wider area, but there is a significant difference in node density between the islands, since the total number of nodes is still fixed; some islands include most of the nodes whereas others are not (Fig. 10 (c) and (d)). For bigger sizes like Fig. 10 (e) and (f), the fixed number of nodes are spread in the bigger area. Therefore, islands get smaller and more widely distributed in the area, and some mobile nodes do not belong to any island. From the results shown in Table II, it is clear that increasing the size of the network is a critical factor that affects the average T_{local}, i.e., as the size of the network gets larger, T_{local} increases for the fixed number of nodes and constant minimum/maximum velocity of mobile nodes. Values of T_{global} in Table II are the twice the minimum T_{local} according to (29). Note that the results of Table II have been well predicted for the case of RWP model (of mobile node).

Table II Local Relocalization T_{local} for 400m×400m-800m×800m areas, for 120 nodes, including 50% mobile nodes

Size (m²)	Total No. of islands	Considerable islands, including more than 5% mobile nodes	Average local Relocalization time among main islands	Global Relocalization Time
400×400	1	1	23.58	46.96
500×500	6	3	31.60	59.50
600×600	>5	4	38.04	72.16
700×700	>10	3	45.98	85.56
800×800	>15	3	54.23	105.88

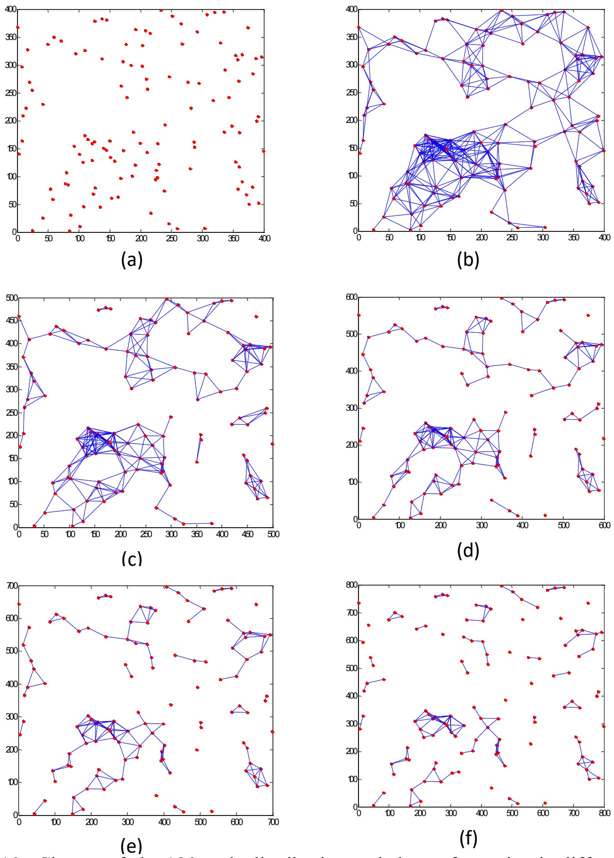


Fig. 10. Change of the 120 node distribution and cluster formation in different network size (a, b) 400m×400m, (c) 500m×500m, (d) 600m×600m, (e) 700m×700m, (f) 800m×800m

As an additional validation, the topology of the network is randomly changed from Fig. 10 (a) to Fig. 11(a) and the proposed TBR algorithm is applied mainly to check its robustness and the applicability for different random topology. The results are demonstrated in Table III and the average T_{local} and T_{global}, show the same trend as shown in Table II.

TABLE III LOCAL RELOCALIZATION TRIGGERING TIME FOR 400M×400M-800M×800M AREAS, FOR 120 NODES INCLUDING 50% MOBILE NODES

Size (m^2)	Total No. of islands	Considerable islands, including more than 5% mobile nodes	Average local Relocalization time among main islands	Global Relocalization time
400×400	2	1	23.58	46.84
500×500	5	2	31.14	62.28
600×600	>5	4	38.01	71.91
700×700	>10	5	47.19	85.05
800×800	>15	4	52.28	100.20

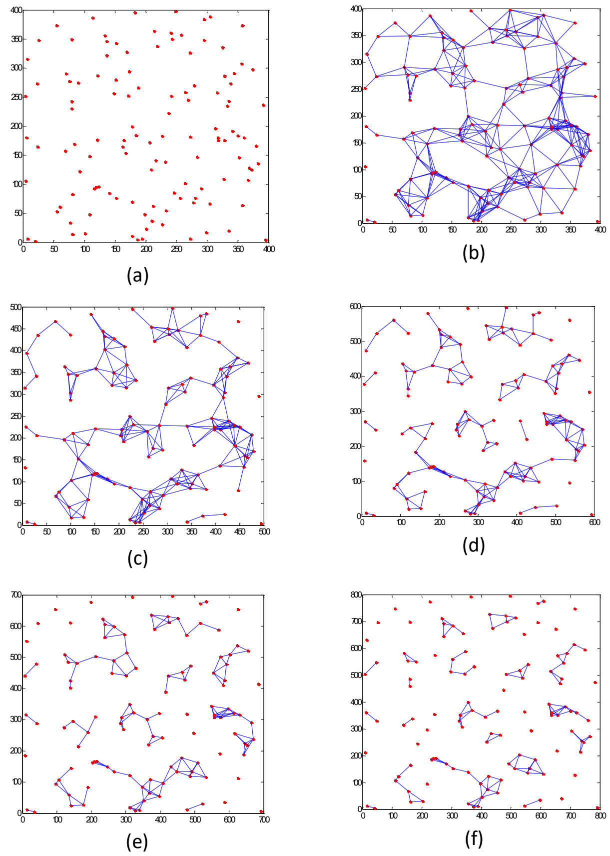
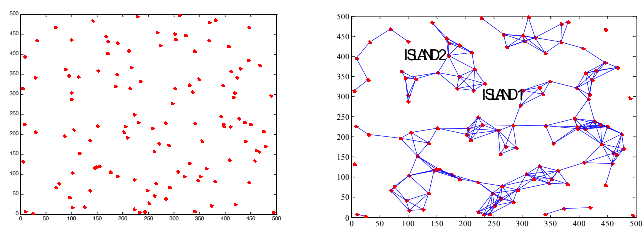


Fig. 11. Another change of the 120 node distribution and cluster formation (from Fig.10) in different network size (a, b) 400m×400m, (c) 500m×500m, (d) 600m×600m, (e) 700m×700m, (f) 800m×800m

The proposed algorithm (Algorithm I) that was tested so far is mainly based on the node velocity and area of the simulation environment that are similar to the main variables used to analytically derive the approximated pdf of relocalization triggering time using RWP model ((16) and (18)). The results of the network simulation reported in Tables I to III show that the estimated local relocalization time T_{local} using network simulation is well matched with the analytically predicted values based on the pdf of the transition time and the smallest variances according to the CRLB. For instance, local triggering time according to Fig. 5, considering network dimensions 400m×400m, 500m×500m and 600m×600m are reported around 29, 33 and 37 seconds respectively, which are comparable to results of Table III that are 24, 31 and 38 seconds. Hence, the resulting T_{global} based on (29) will be accurate enough. In short, results of the network simulations show that having knowledge of the size of the experimental area and the history of the node velocity, the local relocalization triggering time T_{local} can be calculated as well as T_{global} using the proposed TBR algorithm without complicated modeling and analysis of the specific node mobility pattern.

B. Localization Error Reduction using TBR Algorithm

In the previous section A, it is confirmed that T_{global} can be successfully identified using the proposed TBR algorithm. Based on these results, it is necessary to check the effect of the proposed relocalization algorithm on the localization error of the nodes. Fig. 12 (b) shows the random-topology network after information flooding from Fig. 12 (a) which is identical to Fig. 11 (c). Neighboring nodes within the communication range would connect as shown by lines in Fig. 12 (b). Some of the isolated nodes still cannot find any node in their communication range to estimate their locations, therefore, they remain unlocalized. The isolated node can be localized only when it changes its position to a place where more nodes exist within communication range. However, in a dynamic network a node can change its position randomly seeking signal from other nodes. Similarly, the isolated islands with less than 3 anchor nodes are not considered in local error estimation, but considered in global error estimation. As in Fig. 12 (b), there are several islands in the network, but just two of them are considerable, one of them in the middle of the area (which is the main island) and the other is on the top left-side (islands 1 and 2).



(a) (b)

Fig. 12. (a) The selected Random Network topology, (b) Network topology after information flooding

In the network of Fig. 12 (b) (size 500m × 500m), 20 of the sensors are randomly chosen as the anchors, which are used in the localization process [38]. The maximum and minimum speed for the RWP movement patterns are chosen as 25m/s and 5m/s respectively, with no pause time. All trials are run 10 times and average values are reported. Without applying the algorithm for MWSN, it is assumed that the relocalization will start after 200 seconds (T_{fix}), which is twice 100 sec obtained from (12) and the localization error is calculated based on the distance between the last and new estimated locations of each sensor. The relocalization Mean Square Error after T_{fix} is called MSE_{old}. After applying the TBR algorithm again, relocalization Mean Square Errors (MSE_{new}) are calculated at T_{local} and T_{global} that are obtained through the proposed algorithm. To show the effectiveness of the proposed algorithm to decrease the localization error, the error reduction is calculated according to (31).

$$MSE_{\mathrm{Reduction}}\% = \frac{MSE_{old} - MSE_{new}}{MSE_{old}} \times 100 \quad (31)$$

Although the movement pattern is random, the results show an improvement in localization error which is demonstrated by the percentage of error reduction shown in Tables IV-VI, by varying the portion of mobile nodes from 10 to 50%. Tables IV and V show the itemized results of applying the proposed algorithm in the individual main islands of Fig 12 (b) that include more than 10% of the total nodes. In the next step, the whole network is localized at T_{global}, which is derived from (29) and the corresponding error reduction is shown in Table VI. Note that, in all cases of Tables IV and V, the minimum value of T_{local}s always belongs to island 1 (Table IV) which obviously includes more mobile nodes than island 2. Therefore, T_{global}s per each case listed in Table VI should be the twice the T_{local}s of the island 1. On the other hand, increasing the number of mobile nodes leads to lower error reduction and smaller T_{local}. In Fig. 13, the first group of curves in the most left side shows the results of Tables IV-VI.

To observe the algorithm behavior for a longer time, the simulation runs for three additional rounds of global relocalization. Initially, the network topology is the same as Fig. 12 (b). But after each relocalization run the nodes move and the topology changes randomly. The results in Fig. 13 show the MSE reduction versus percentage of mobile nodes (between 10 to 50%). In Fig. 13, the second group of curves show the results of the second global relocalization round and so on. Observing the change of MSE for successive rounds proves its effectiveness in reducing the localization error for a longer time and shows that maximum MSE reduction is less than 35% for different percentages of mobile nodes but more than 5%. In other words, MSE reduction is bounded between 5 to 35% by applying the proposed TBR algorithm and the highest value belongs to the case with the least number of mobile nodes, due to the existence of the small number of unlocalized nodes.

TABLE IV T_{LOCAL} FOR ISLAND 1 AND % OF ERROR REDUCTION USING RWP MODEL

Number of mobile nodes	Error reduction	T_{local} (sec)
10%(12 nodes)	27%	31
20%(24 nodes)	26%	31
30%(36 nodes)	24%	30
40%(48 nodes)	12%	30
50%(60 nodes)	9%	29

TABLE V T_{LOCAL} FOR ISLAND 2 AND % OF ERROR REDUCTION USING RWP MODEL

Number of mobile nodes	Error reduction	T_{local} (sec)
10%(12 nodes)	27%	39
20%(24 nodes)	25%	33
30%(20 nodes)	24%	35
40%(48 nodes)	13%	33
50%(60 nodes)	7%	33

TABLE VI GLOBAL ERROR REDUCTION PER T_{GLOBAL} USING RWP MODEL

Number of mobile nodes	Error reduction	T_{global} (sec)
10%(12 nodes)	32%	62
20%(24 nodes)	29%	62
30%(36 nodes)	26%	60
40%(48 nodes)	13%	60
50%(60 nodes)	11%	58

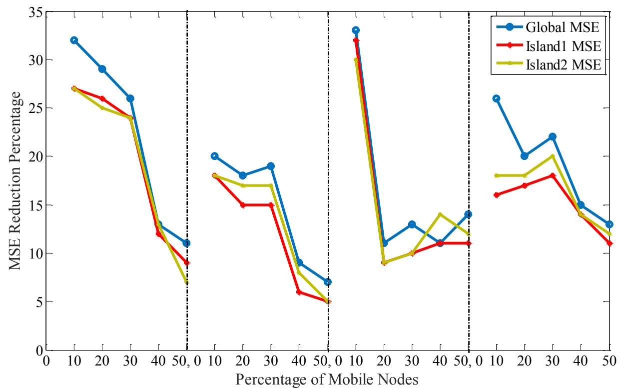


Fig. 13. MSE behavior for four relocalization rounds using RWP pattern

To show the reliability of the proposed algorithm, the algorithm is also applied to two other movement patterns: Levy walk [30] and Brownian motion [24]. Results of four successive relocalization rounds show the significant error reduction in localization error as the case of RWP model.

Fig. 14 shows the MSE reduction after four successive relocalization rounds using Levy Walk pattern. The percentages of MSE reduction are bounded between 15 and 60%. Similar to the case of RWP model, the highest value belongs to the networks with 10% mobile nodes. Note that, since movement models are random, no identical curves for all rounds can be expected.

For the Brownian movement pattern, the default time duration is the same as the RWP pattern. Fig. 15 shows the significant reduction of MSE for Brownian model due to the nature of this movement pattern, where small fluctuations around last location lead to the smaller differences between MSE reduction values for different percentages of mobile nodes compared with the RWP and Levy models.

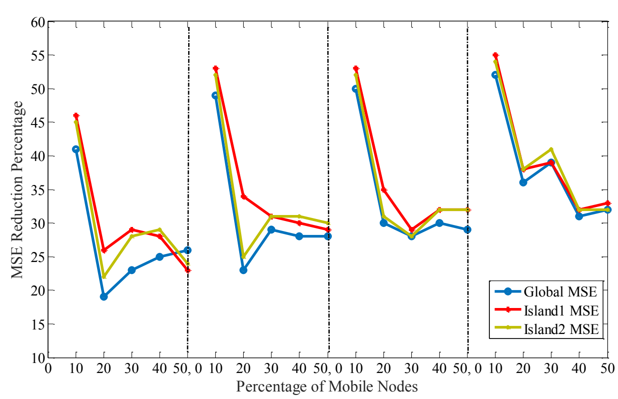


Fig. 14. MSE behavior of four global relocalization rounds using Levy walk pattern

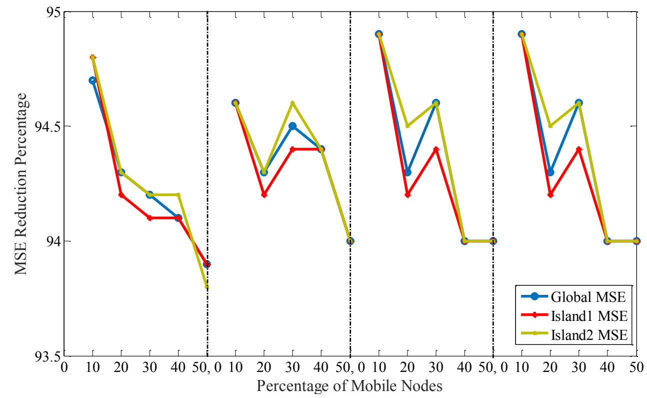


Fig. 15. MSE behavior for four global relocalization rounds using Brownian motion

V. Conclusion

In this paper, the TBR algorithm was proposed, which can provide the best estimate of the global network relocalization time for the MWSN considering the node mobility patterns including random waypoint as well as the Levy walk and Brownian motion. The accuracy of the proposed method was initially checked by the mathematical analysis to yield the probability density function of RWP that eventually leads to approximate a pdf function for relocalization triggering time. Additionally, its soundness is checked by Cramer Rao Lower Bound (CRLB). The identified global relocalization time, which is based on the local relocalization time per island, is an optimum time interval to retrigger localization process which yield minimum localization error across the individual islands of nodes as well as the entire network. This is achieved by calculating the optimal time limit before starting relocalization by considering physical parameters of the network and node's movement history. The performance of the proposed algorithm was thoroughly checked for the random-topology network by computer simulations with varying network parameters including the number of nodes and the size of the network. Results of the network simulation show that the application of the proposed algorithm increases network performance by decreasing the accumulated localization error in all scenarios tested, up to 32% for RWP movement pattern. To check the applicability of the proposed algorithm for the extended time duration, two additional mobility patterns of Levy walk and Brownian motion were used and the simulation results also support the effectiveness of the proposed TBR algorithm.

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