Adaptive self-localized Discrete Quasi Monte Carlo Localization (DQMCL) scheme for wsn based on antithetic markov process

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Abstract— Most of the localization algorithms in past decade are usually based on Monte Carlo, sequential monte carlo and adaptive monte carlo localization method. In this paper we proposed a new scheme called DQMCL which employs the antithetic variance reduction method to improve the localization accuracy. Most existing SMC and AMC based localization algorithm cannot be used in dynamic sensor network but DQMCL can work well even without need of static sensor network with the help of discrete power control method for the entire sensor to improve the average Localization accuracy. Also we analyse a quasi monte carlo method for simulating a discrete time antithetic markov time steps to improve the life time of the sensor node. Our simulation result shows that overall localization accuracy will be more than 88% and localization error is below 35% with synchronization error observed at different discrete time interval.

Keyword- Localization, WSN, Discrete Power, QMCL, Antithetic Markov chain, Variance reduction method

I. INTRODUCTION

Wireless sensor network are tremendously being used in various applications that include[1] target tracking,rescue,disasterrelief,habitat monitoring and number of tasks in smart environments[2].so localization is an important to identify the location of the sensor which detect the events from geographical area [3].In general GPS has not support in to WSN very well due to the power consumption of GPS will reduce the entire battery life of the sensor node and also reduce the effective lifetime of the entire sensor [4] network.so we need to develop a standard localization algorithm to overcome this limitations and find the alternative method that rely on the measurements of distance between them.

In general the distance could be calculated based on some high level parameters of WSN, (i.e.) time of arrival, time difference of arrival Or received signal strength[5].The time of arrival, time difference of arrival make use of signal propagation time for determining the distance between the sensor node and RSSI coverts the signal strength in to distance.Montecarlo localization[6] is a version of markov localization, a family of probabilistic approaches to determine the position of sensor given a map of it is environment. Based on this Monte Carlo method so many Localization algorithms have been proposed in the past several years [2,7,8].In these algorithms are based on Monte Carlo method they may either suffer from low localization accuracy, high becon density and high localization error,Esspecially in sequential Monte Carlo localization [9] is suffer from low sampling efficiency Or high power consumption.

To overcome this all limitations, In this paper we propose a new analytical model for localization using quasi Monte Carlo method [21,22], to improve the performance of the Monte Carlo simulations ,offering shorter computational times and higher accuracy. Based on this QMCL ,we develop DQMCL algorithm for WSN based on antithetic markov model, which variance reduction method to improve the accuracy of MCL,AMCL,SMCL.In our proposed method (DQMCL),The markov random field is n dimensional random process defined on a discrete lattice, which attempts to reduce the variance by introducing negative dependence between the sensor of replication.in this technique we generate n number of distributed samples $Y_1, Y_2 \ldots\ldots Y_n$ for each sensor and let the unbiased estimator for $\hat{\theta} = Y_1 + Y_2 + \ldots\ldots + Y_n / 2$ if and only if $\mathrm{cov}(Y_1, Y_2, \ldots\ldots Y_n) < 0$ .In DQMCL,We assume our channel model an ergodic discrete markov chain $M_i(t)$

taking values in a set $M_i = \{1, 2, ...X_i\}$ of x_i states with transition probabilities P^i_{xy} .The markov chain $M_i(t)$, i=1……N,Are assumed to be independent and discrete times t that are non-integers. In our model we consider time heterogeneous markov chains such that

Ƥ[Y_{n+1}= j | Y_n] = Ƥ [Y_1 = =j | Y_n] for all j ε E and n ε N.

To characterize these heterogeneous chains it's then sufficient to have initial distribution $\mu = (\mu\{i\} : i \varepsilon E)$ with μ{i}= Ƥ [Y_0=i] and the transition matrix of the sensor P = (p(i , j) : i , j ε E) with P(i , j) = Ƥ(i , j) = Ƥ [Y_1=j | Y_0=i].We also assume $\hat{I}$ is a unbiased estimator to calculate Localization error in the estimator $\hat{I}$ is given by the antithetic sample variance S^2 ,Where

$$S^2 = \frac{1}{(N-1)} \sum_{i=1}^{N} [g(\vec{x}_i) - \hat{I}]^2 \tag{1}$$

Where N is Total number of sensor and $g(\vec{x}_i)$ is Gaussian heterogeneous coverage area.S^2 is also used to evaluating the accuracy of quasi Monte Carlo localization over MCL, SMCL, AMCL and other methods

II. RELATED WORK

The major problem to deploy the node of WSN is coverage. This coverage area of sensor nodes would based on the distance between the two different nodes.so the location information is the basic input for all the localization algorithm that determine the coverage of the network [11]. Most of the existing localization algorithms are based centralized or distributed manner.in general centralized algorithms [12, 13, 14] has computed their location more accurately, so it can be suitable in the place where accuracy is important. And on the other hand distributed algorithms[15,16] potentially have better scalability but accuracy is low compared than centralized approaches.Esspecially in MDS-MAP centralized algorithm that uses information of node connectivity to analyse the location of node that fit those predefined distances and finally they have returned to an original normalized result of any node whose position are known.in this algorithm accuracy is good but the messaging and computational cost is very high.in some range free centralized algorithm[17,18,19] to make the scheme cost effective then range based approaches, that can be reduced the cost and provide good localization estimate but accuracy is low and also need extra hardware requirement.in [20],the authors developed TISNAP technique to improve the localization accuracy .but in this method authors has used single source localization process to achieve the good localization accuracy.

In some distributed based localization algorithms [16] the localize sensor node in a region by the use of robust quadrilaterals. Each node measures the distances of the neighbouring nodes and form a cluster in some local coordinate system.so every node need more energy to collect the data from cluster.in this technique anchor nodes can change their communication range by increasing their transmitting power.to overcome these all limitations of distributed and centralized algorithms monte carlo [6], sequential monte carlo [9], adaptive monte carlo[10] and dual and mixture monte carlo methods[11] has been proposed. But these all algorithms have suffer from low sampling efficiency, high computational cost and high beacon density. Although of all above monte carlo methods the localization error rate is decreases with respect to number of samples (i.e.) monte carlo integration is proportional to $1/\sqrt{N}$ .this means that to halve the error, four times as many samples is needed.

But in our proposed DQMCL method uses sequences of quasi random numbers which have a more uniform behaviour to compute the number of sampling in order to increase the localization accuracy. This change will cause the sampling estimate to converge towards the actual solution like $(l\,\mathrm{n}\,N)^s / N$ where S is the number of dimensions instead of the usual $1/\sqrt{N}$ of the standard MC procedure .also we use some antithetic variables to reduce the computational time and increase the efficiency of the algorithm. By using this variance reduction method all the sensor nodes can increase the accuracy of it is estimation by repeating the packet exchange to obtain multiple number of estimates out(t_0),out(t_1),….out(t_{n-1}).so for the system model each out(t_k) can be represented as $out(t_k) = I_{po} + \omega(t_k)$ .where $\omega(t_k)$ is sampled form of discrete Markov chain .and I_{po} be the initial phase offset at time t_k.For unbiased antithetic minimum variance estimation can be calculated for I_{po} is $\hat{I}_{po} = \frac{1}{n}\sum_{k=0}^{N-1} Out(t_k)$ .the probability density function of making the observation out(t_0), out(t_{n-1}) for assumed known parameter initial phase offset I_{po} and antithetic variance σ_X^2 / n can be written as

$$p\left(out(t_1),.....,out(t_{n-1});I_{po},\rho_x\right)=\sum_{i=0}^{n-1}\frac{1}{\sqrt{2\pi\sigma_X^2}}\exp\left[-\frac{(out(t_i)-I_{po}-\rho_x t_i)^2}{2\sigma_X^2}\right] \quad (2)$$

This observation of time steps is based on a posteriori Gaussian markov model [23].

III.PROBLEM FORMULATION

In our localization model we have consider a heterogeneous wireless sensor network with discrete markov chain $\{X_1, X_2.....X_n, n\varepsilon N\}$ with state space of geographical area G.The total probability that the discrete markov chain with n number of steps with state i, that is

$$\lambda_n\{i\}=P[X_n=i]=\lambda_0 p^n\{i\} \quad (3)$$

Where the distribution λ_0 has the initial state X_0 with transition matrix of p(i,j)is

$$p(i,j)=P[X_n=j\mid X_{n-1}=i] \quad (4)$$

In our network graph model as an abstract tuble consists of a collection of vertices and edges (i.e.) G=(V,E).Each and every edges eεE join with more than one sensor node which act as multihop communication with e=< u,v > where u and v is the adjacent vector of discrete Gaussian markov model. For any network graph G with neighbour node of vertex is twice the number of edges. That is $\sum_{V\varepsilon V(G)}\delta(v)=2.|E(G)|$.The overall time measurement history up to time t is denoted as $T^{(t)}=\{T^{(0)}, T^{(1)},\ldots T^{(t)}\}$.With assumption of graph G we consider the sensor position in three dimensional angle with (x_i,y_i,z_i) where i=1,2,…N and unknown position of sensor can be represented as (x_u,y_u,Z_u) where u=1,2,….M,with the perfect distance values r_i , i=1,2,……R.The transition matrix of the above assumption is

$$\left[x_1,x_2\ldots\ldots\ldots x_N \quad y_1,y_2\ldots\ldots\ldots y_N \quad z_1,z_2\ldots\ldots z_N\right]\left[x_{u1},x_{u2}\ldots\ldots\ldots x_M \quad y_{u1},y_{u2}\ldots\ldots y_M \; z_{u1},z_{u2}\ldots\ldots z_M\right]=\left[r_1,r_2\ldots\ldots\ldots r_R\right] \quad (5)$$

All the sensor power has been considered as discrete time markov chain X_i with finite state space S.For K step transition probabilities are

$$P_{i,j}^{(k)}=pr(X_{t+k}=j\mid X_t=i)(i,j\varepsilon S) \quad (6)$$

With finite discrete power of

$$\sum_{j\varepsilon S}\pi_j=1\&\sum_{i\varepsilon S}\pi_i p_{i,j}=\pi j \text{ for Every } j\varepsilon S. \quad (7)$$

The following assumption we made in our network model to analyse the position of sensor node

- Uniformly select an edge eεE with respect to the position of sensor node
- Let C Denote the cycle of X_tU{e}
- Choose an edge e' uniformly at random from C and finally set $X_{t+1}\leftarrow(X_t U\{e\}\setminus\{e'\})$

Suppose π is a variate with three dimensional Localization conditionals $\pi_i(x_i\mid x_{[-i]})$ from which possible to samples of all discrete values i=1,2,….d.The localized information can be arrives at the base station according to a non-homogeneous Gaussian Poisson process with intensity function λ(t) at t ≥ 0.The arrival and departure time of localization information is assigned as $TOA_{Loc.T}(i)$ and $TOD_{Loc.T}(i)$ respectively. The aperiori probability is assigned by T_p which represented as the time of past T that the last localized information leaves the system.

IV. ANALYTICAL MODEL FOR DQMCL

In our analytical model, first we establishing our notations and localized terminology. Here we have consider antithetic discrete time markov chain $X_0,X_1,X_2\ldots$, where each X_i takes value in a discrete power of finite sensor with geographical area G for k step multihop communication of $P_{i,j}^{(k)}$ is the $(i,j)^{th}$ entry of P^k.in our discrete markov model the signal can get from each hop to every other hop of sensor. The overall hop count for every $i,j\varepsilon G$ there exists at k≥0 such that $P_{i,j}^{(k)}>0$.Let D be a distance between the each sensor with respect of position G.the calculation of D is based on aperiodic probability of markov chain.

The goal of DQMC Localization Is to get a perfect estimation of target state $X^{(t)}$ from the measurement history $Z^{(t)}$.Let P(X) is denote a priori probability distribution function of the state Then P(Z|X) is likelihood function of

Z ,and P(X|Z) is a posteriori of The fundamental relationship between this all function is represented by Bayes theorem,

$$p(X \mid Z) = \frac{p(Z \mid X)\,p(X)}{\int p(Z \mid X)\,p(X)dx} = \frac{p(Z \mid X)\,p(X)}{p(z)} \tag{8}$$

Where p(Z) is the normalized constant so we only compute $p(Z \mid X)\,p(X)$ .to solve this notation we can rewrite the Bayes rule as $p(X \mid Z) = kp(Z \mid X)\,p(X)$ .Under this assumption and based on this new measurement the sensor node computes a posteriori distribution of new measurement $Z^{(t)}$.(i.e.)

$$p(Z^{(t)} \mid X^{(t)}) = \prod_{i=1,\ldots,k} p(Z_i^t \mid X^{(t)}) \tag{9}$$

This DQMCL method utilizes all K measurements at every time steps with new positions $X^{(t)}$.

In order to exemplify the concept, we take the problem of dynamic Localization position with time invariant sensor characteristics. So In DQMCL we assume some few sensors are beacon sensors measuring strength of the signal so that the state vector $X=[x,y,z]^T$.The measument of Z may be assimilated over discrete time,either by a single or multihop sensor which is denoted by $Z^{(t)}$.the previous measurements of sensor state can be calculated by means of Gaussian a periori probability at time t it takes a new state measurements of $Z^{(t1,t2\ldots.t_n)}$ .Our analytical model will follow the following steps to calculate the overall behaviour model of the network.

- First we Start with a discrete sampled power representation of the senor node up to observation i-1 and j-1
- Use the quasi monte carlo integration rule to constitute the markov predictive distribution as a finite distribution model.
- Use quasi event sampling with the predefined markov event distribution to predict the previous states of sensor up to observation i.

V. DISCRETE QUASI MONTE CARLO ADVANCED INTEGRATION RULE

The general principal of quasi monte carlo method which always possible to determine the prescribed level of accuracy by using advanced integrated rule.so it achieve higher localization accuracy over than other monte carlo method. The basic function of quasi Monte Carlo integration rule are taken from the Monte Carlo estimation. Let consider the geographical position 'G' unit cube integration domain $I^s = [0,1]^s$,So the approximation of QMC is $\int_{I^s} f(x)dx \approx \frac{1}{N}\sum_{ki=1}^{N} f(X_k)$ .Instead of MCL method, We can use deterministic nodes $x_1, x_2, \ldots x_N \varepsilon I^s$ .To reduce the overall localization error we can described here is antithetic variables Monte Carlo (i.e.)

$$A = \frac{1}{2N}\sum_{k=1}^{N}[\,f(x_k) + f(2C - x_k)] \qquad \text{Where } C = \left(\frac{1}{2},\ldots.,\frac{1}{2}\right)^T \text{ is the center of } I^s \tag{10}$$

The number of calculated antithetic variables of MC is related to the dimension of S.Based upon this assumption 'T_{Loc}' denotes the overall time for entire localization system.Loc_{tA} and Loc_{tD} is the event list of sensor information from one hop to another hop which in heterogeneous media and t_A is the time of next state packet information and t_D is the hop completion time of each sensor. Suppose the system is idle then t_D is set to ∞.the TOA process of our DQMCL model is described below.

Assumption:

$TOA_{Loc.T}(i)$ =Localized information arrival time

$TOD_{Loc.T}(i)$ =Localized information Departure time

$T_{p.Loc}$ =Time of past information that last transmitted data leaves from the system

Initialization

$LocN_A$ and $LocN_D$ =Number of hop arrival and departure respectively by time T_{Loc}.

Set $t = LocN_A = LocN_D = 0$

Set $n = 0$

Generate T_0 ,Set $t_A = T_0$ and $t_D = \infty$

Phase I

Move along the time axis and update the Localization system if new hop occurs

Condition: $t_A \le t_D, t_A \le T_{Loc}$

Reset $t = t_A, LocN_A = LocN_A + 1$ and $n = n + 1$

Generate new Localized arrival time T_t and Reset $t_A = T_t$

If $n = 1$ then

Generate Y and reset $t_D = t + Y$

Collect the system output data - $A(LocN_A) = t$

Phase II

Condition: $t_D < t_A, t_D \le T_{Loc}$

Reset $t = t_D, LocN_D = LocN_D + 1, n = n - 1$

If $n = 0$ then

Reset $t_D = \infty$,else

Generate $Y - G$ and reset $t_D = t + Y$

Collect output of $D(LocN_D) = t$

Phase III

Condition: $\min(t_A, t_D) > T_{Loc}, n > 0$

Reset $t = t_D, LocN_D = LocN_D + 1, n = n - 1$

If $n > 0$ then

Generate $Y - G$ and reset $t_D = t + Y$

Collect $D(LocN_D) = t$

VI. DQMCL SAMPLING EFFICIENCY

The Sampling method of DQMCL method give much smaller error than normal monte carlo methods with the same sample size.in our localization method we have taken two properties of QMCL method to improve the efficiency of algorithm. The first method is a sampling smoothing method which based on accepting and rejection method. The main drawback of QMCL is often lost on problems involving if the samples are discontinuities. But in our DQMCL sample model the general acceptance –rejection method is slightly modify by using advanced integral QMCL method. That is integrate of a function f multiplying a function P on the unit interval with $0 \le p(x) \le 1$.then

$$\int_0^1 f(x)p(x)dx = \int_0^1\int_0^1 f(x)\aleph(y < p(x))dydx \qquad (11)$$

With weight of accepting samples $W_{accept} = \aleph(y < p(x)) = 1$ if and only if $y < p(x)$ (12)

And weight of rejection method $W_{Rejection} = \aleph(y < p(x)) = 0$ if and only if $y > p(x)$ (13)

So the quasi monte carlo quadrature will be $I_N = N^{-1}\sum_{i=1}^{M} W_i f(x_i)$ Where $N \approx \sum_{i=1}^{M} W_i$ This equation is formulated by replacing discontinuous sampling function $\aleph(y < p(x))$ by a smooth sampling function q(x,y) satisfying $\int_0^1 q(x,y)d\,y = p(x)$ and sampling procedure is sample (x,y) dimension uniformly and set the weight

W=q(x,y) and repeat until $\sum_{i=1}^{M} q(x_i, y_i) \approx N$ .By using this formula, the smoothed acceptance rejection samples of DQMCL method is given by

$$J_N = N^{-1}\sum_{i=1}^{M} q(x_i, y_i)\, f(x_i) \text{ in which } \sum_{i=1}^{M} q(x_i, y_i) \approx N . \quad (14)$$

The second method of sampling is resampling procedure of N sensor particles implies of probability distributions $\{r(.|W), W\varepsilon[0,1]^N\}$ on $\{1,....,N\}^N$ .This resampling method is very essential for DQMCL technique to rearranging the dimension of weight W.So it will produce a sequence of samples $\{X_n{}^i, i = 1,..., N\}$ for n=1,…,T.For homogeneous sensor network our DQMCL method will follow the following QMC sampling Procedure.

- Sample $X_1^{(i)} \sim q_1(.)$
- Update and normalize the weights $W_1^{(i)} = \dfrac{W_1(X_1{}^i)}{\sum_{k=1}^{N} W_1(X_1{}^k)}$

  For heterogeneous WSN,
- Sample $A_{n-1} \sim r(.|W_{n-1})$ and $X_n{}^i \sim q_n(.\,|\, X_{n-1}^{A_{n-1}^i})$
- Then set $X_n{}^i = (X_{n-1}^{A_{n-1}^i}, X_n{}^t)$
- Finally update and normalize the weight of samples (i.e.) $W_n^i = \dfrac{W_n(X_n^i)}{\sum_{k=1}^{N} W_N(X_n^k)}$

A. Computational time of DQMCL method

From the DQMCL sampling, we have formulated the correlated sampling between different sensors to reduce number of computation. Let $I_1 = \int f_1(x) g_1(x) dx$ and $I_2 = \int f_2(x) g_2(x) dy$ .the difference between the two primary sensors is $\Delta = I_1 - I_2$ .From the observation select N values of X from $f_1(x)$ and N values of Y from $f_2(x)$.(i.e.)

$$f_1(x) = X_1........X_N \quad \text{And} \quad f_2(x) = Y_1........Y_N \quad (15)$$

Then compute $\widehat{\Delta} = \widehat{I_1} - \widehat{I_2}$

$$= \frac{1}{N}\sum_{i=1}^{N}[g_1(x_i) - g_2(y_i)]$$

$$= \frac{1}{N}\sum_{i=1}^{N}[g_1(x_i) - \frac{1}{N}\sum_{i=1}^{N} g_2(y_i)] \quad (16)$$

The variance of $\widehat{\Delta}$ is given by

$$\sigma^2(\widehat{\Delta}) = \sigma_1^2(\widehat{I_1}) + \sigma_2^2(\hat{I}_2) - 2\operatorname{cov}(\widehat{I_1}, \widehat{I_2}) \quad (17)$$

Suppose if the random variable $\widehat{I_1}, \widehat{I_2}$ are correlated in positive manner, then $\operatorname{cov}(\widehat{I_1}, \widehat{I_2}) \geq 0$.

So the correlated sample is identified and reduce computation time of overall sample process.

VII. DISCRETE ANTITHETIC QMC

In order to deduce the power consumption of sensor node we use discrete power control method with the help of antithetic variance reduction method. Let consider the equation (1) to measure the accuracy of Localization in terms of quasi Monte Carlo method.

$$S^2 = \frac{1}{(N-1)}\left\{\frac{1}{N}\sum_{i=1}^{N} g^2(\vec{x}_i) - \hat{I}^2\right\} \tag{18}$$

S^2 is an estimate for variance of $\hat{I}$ .the estimation can be shown that

$$E[S^2] = E[(\hat{I} - I)^2] = \frac{\sigma^2}{N} \tag{19}$$

Where σ^2 is the variance of $g(\vec{x}_i)$ and N is the total number of hop per cycle. To evaluate the efficiency of localization we have taken two hop count of σ_1^2 and σ_2^2 .It is desired that the estimate $\hat{I}$ fall in the interval $I-\varepsilon$ to $I+\varepsilon$ .The computational effect can be calculated by using two hop information of sensor which state that $N_1 = k^2\sigma_1^2 / \varepsilon^2$ and $N_2 = k^2\sigma_2^2 / \varepsilon^2$ .Let the localization time taken per hop is t_1 and t_2 respectively. The corresponding efficiency is calculated by ratio of these t_1 and t_2 will be,

$$\text{Efficiency=}\ \xi = \frac{t_1\sigma_1^2}{t_2\sigma_2^2} \tag{20}$$

However it's reasonable to replace then by their estimators and get an estimator for ξ ,

$$\hat{\xi} = \frac{t_1 s_1^2}{t_2 s_2^2} \tag{21}$$

Where $S_1^{\ 2} = \frac{N_1}{N_1^{-1}}\left\{\frac{1}{N_1}\sum_{i=1}^{N} g^2(\vec{x}_i) - \hat{I}^2\right\}$

In our DQMCL model, the power can be calculated in terms of discrete. So each sensor has own allocation of sample schedule per hop at the same time sensor can only select one event at any particular point of time. So each sensor simply divide their power depends upon the event.The Computational time of DQMCL method can be calculated as follows

If S is a sensor measurement of x,y then

$$\xi = \frac{t_1\sigma_1^2}{t_2\sigma_2^2}$$

For all z do

Loc(y) ← P(z|x)Loc(x)

$$\xi = \frac{t_1\sigma_1^2}{t_2\sigma_2^2} + Loc^{'}(x)$$

For all z do if and only if

$$Loc^{'}(x) \leftarrow \xi^{-1} Loc^{'}(x)$$

Then

$$Loc^{'}(x) \leftarrow \int P(x, y \mid z) Loc(x^{'}, y^{'}) dx^{'} dy^{'}$$

Return $Loc^{'}(x)$

The power management mechanism of QMCL directed by some criteria to save energy consumption in sensor node. Within a single computational time to find the optimum policies which minimize the power consumption model by using markov decision process.so the dynamic states of the entire system can be effectively captured by markov chain. The power consumption model of DQMCL is extended from a supervisor node to the whole network in determining the how much of power is needed to track the object.

VIII. PERFORMANCE EVALUATION

In this section, we evaluate the performance of DQMCL method through extensive simulation. In order to evaluate our contribution we are concentrating on the following parameters to improve the overall performance of our algorithm.

- Localization Error
- Life time of the sensor
- Localization accuracy
- Computational Time

These all high-level parameters of our method is compared with existing Monte Carlo based localization method (i.e.) MCL, AMCL, SMCL.In our model we assume all the nodes are uniformly deployed is a 400 units * 400 units square area and communication range r is set to be 200 units. Figure 1 shows the node deployment of sensor nodes in L*L Square area.

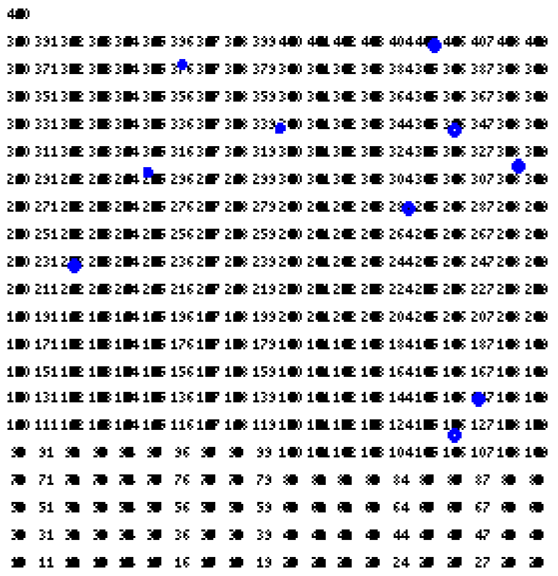

Fig (1)

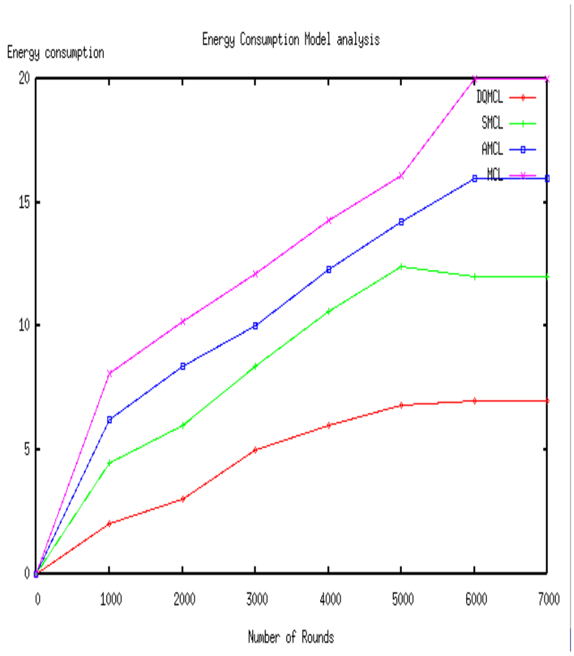

Fig 2(a)

In a first set of experiments the energy consumption model of our DQMCL was compared against the other MCL based method. Figure 2(a) shows that energy consumption model of the DQMCL compared with other three Monte Carlo localization method. The Increase rate of energy consumption of our proposed method is lower than the energy rate of MCL, AMCL, and SMCL.

In figure 2 (b) shows the nodes alive of our proposed system is much better than other method. Besides both the dead time of first and last node of DQMCL method are later than Existing method. So all the sensor can get longer life to receive the data by using our proposed method.

In the second set of experiments, the computational time of our method was compared with other existing method. In general as the number of nodes increase in a sensor network the time of computation needed to localize the nodes also increses.As shown in figure 3(a) and 3(b),The computational time of DQMCL increases linearly with respect to the network size.as the number of wireless nodes increses,Existing Localization algorithm will not able to provide good Localization accuracy as it takes more time to localize the wireless node, thus providing out dated location estimation. On the other hand DQMCL demonstrated a very small increase in execution time with respect to network size, thus providing up to date accurate results.

In a third set of experiments, The Localization error of our DQMCL method was compared with existing localization method. Figure 4 shows the localization error of the sensor node for different network size, with same number of execution time. The DQMCL method provides better result than other methods. This is because since DQMCL takes less time to execute, The Location information at the beginning of each interval is more up to date and more accurate, Thus resulting in a Lower localization error.

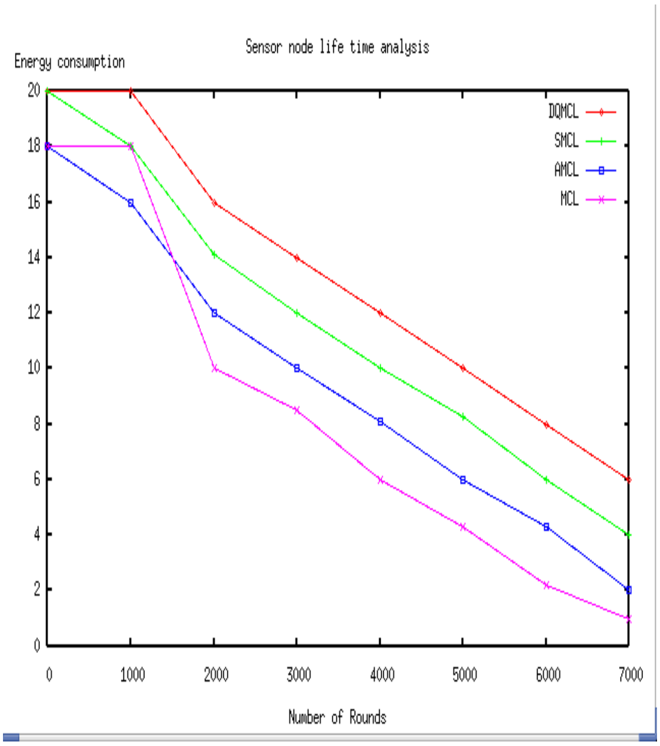

Fig 2 (b)

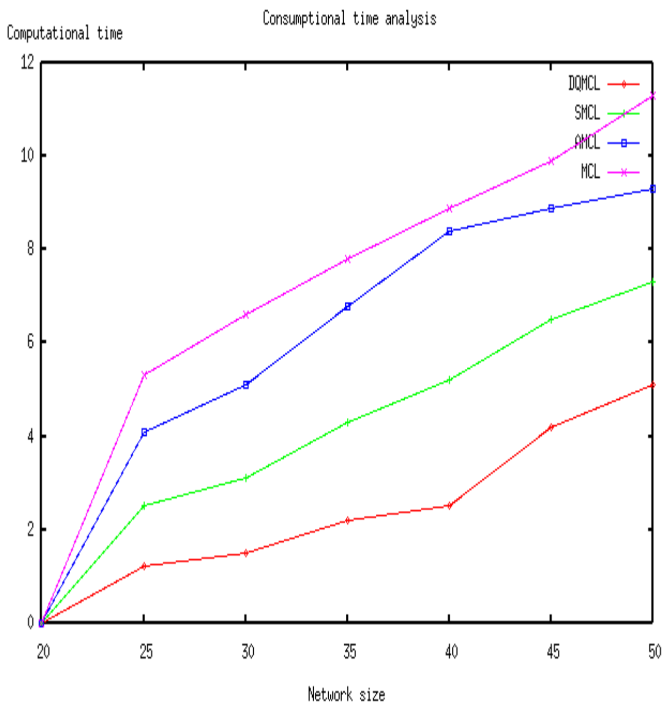

Fig 3 (a)

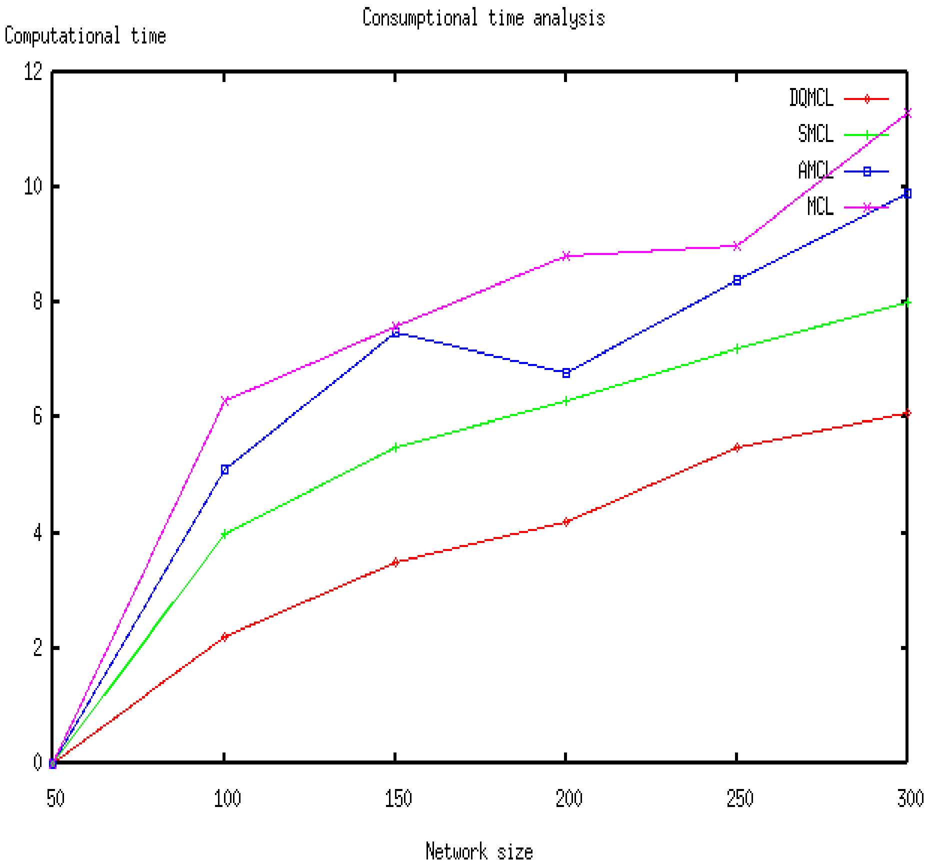

Fig 3(b)

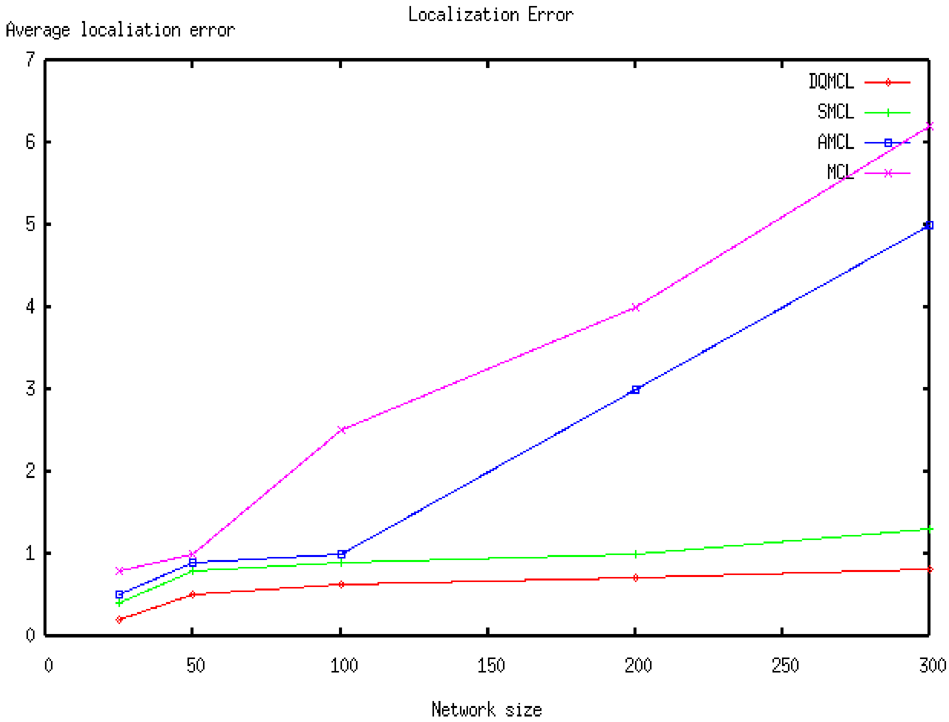

Fig (4)

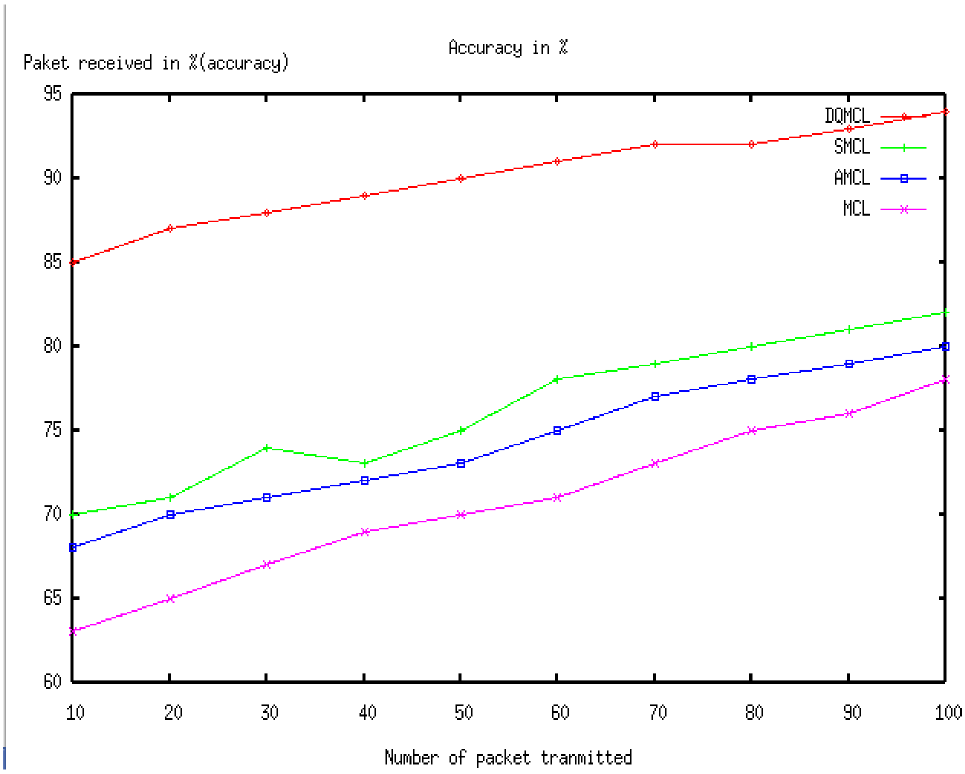

Fig (5)

Figure 5 shows that the overall accuracy of DQMCL method is more than 85% compared than other MCL based localization when number of packets transmitted in heterogeneous area. However the packet size is below 10,the localization accuracy is maintain 80-85%.

IX. CONCLUSION

In this paper, we develop a self-localized discrete quasi monte carlo method for heterogeneous WSN. In this method we achieve good Localization accuracy by using advanced discrete time integration rule of quasi monte carlo method. In our method we analyze the infrastructure and geometric method by investigating the high level parameters of WSN. Also we analyze a quasi Monte Carlo method for simulating a discrete time antithetic markov time steps to improve the life time of the sensor node. The Localization error of the new algorithm is smaller than the error of standard Monte Carlo algorithms like MCL, AMCL and SMCL. Our simulation result shows that overall Localization accuracy will be more than 88% and Localization error is below 35%.

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