FUSION BASED SENSOR NODE DYNAMICALLY MEASURE QUANTIZED DATA FOR TARGET TRACKING

Dr. G. Kavitha, Dr. G. Kalaimani

Abstract: This paper focused on extending the earlier work of the sensor node selection process. Focus on more challenging issues by utilizing the effective quantized data for tracking the target sensor network by considering the selecting problem with the quantized sensor data. In the proposed, scheme received signal strength indicator (RSSI) this is based on the sensor node position. From the reference fixed nodes and tags are placed at the know positions by utilizing the radio signal radiations to generate an accurate model of signal propagation. To perform the optimized tracking system are dynamically selecting the subset of sensors. The one step-look ahead posterior method of Hybrid Backpropagation Rate Bound (HRBR) used to measure the sensor selection of state estimating the error are proposed. To compute the posterior method of HRBR are employed Particle filtering as well as estimating the target selection state. Simulation results show the proposed posterior HBRB based on the method outperforms by accurate target tracking by selecting a quantized node.

Keywords: Sensor Network, Target Tracking, Hybrid Backpropagation Rate Bound (HBRB), Particle filtering, RSSI.

I. Introduction

In previous work, the proposed method the optimal set to participated in the target tracking of the sensor nodes selection process. It was assumed by providing the information by each set of the sensor was perfect and complete. It required the high communication cost by the substantial energy consumption of sensor nodes. However, in sensor data of real systems are communicated over the bandwidth-limited of channels. So, it is critical to consider the problem of transforming the quantized data. Tracking of sensor nodes is always based on the quantized summation sensor.

The framework of target tracking utilized the quantized sensor data are transmitted over the noisy channels between the fusion center and sensors. In the proposed system, based on the measurement of fusion and intelligent quantified of delta modulations. Each sensor designs dynamically to quantize according to the process of updating the tracking target state are an estimate to send from the data fusion center. By focusing on the problem is occurred in selection of subset of the sensor are maximized by tracking the performance of measuring quantized sensors. Each sensor employs to assume the same uniform function of quantization schemes.

In exist there are many sensor nodes of the selection algorithm approach are processed. Among them, the information-driven based method is the most popular. The main idea of selecting the sensors provides the most useful information which is measured by mutual or entropy information. However, each node is decoupled by measuring the information-theoretical are selecting more than one node of sensors to imply the total number of information measured via the sum of the individual measure of sensor information.

Regarding the intention tracking state, a set of senor collectively gives the more information rather than the highest stand-alone data measured with the choice of greedy based method of information-theoretical process. The proposed system for HBRB used for two reasons are achieving the approach. First, the target tracking accuracy in term of achieving the centralized bounded data for backpropagation. In computing the threshold backpropagation utilized to measure the target of the quantized node. Second, the HRBR posterior method based choosing the set of sensor node which collectively reduce the estimation of errors.

II. Related Works

Over the past year for estimating the mobile location are much interested and attracted [15]. This was required by the FCC rule-based method suggested to the cellular networks this provides emergency call in the locations. In [13], the location-based application causes the ranging error in the indoor wireless process often performed under the non-line of sight (NLOS). This application greatly benefits from the identification of NLOS and improving techniques. These methods primarily investigated in the ultra-wideband (UWB) method. But the little attentions have been applied to WI-Fi systems, which are more prevalent in far practice.

In this study, they address the NLOS [9, 12] mitigation and identification problems used in the multiple RSS measurements from the WI-Fi signals. The key exploits the several approaches for statistical features from the RSS series times, which are shown, to be particularly effectual [3]. The author compares and develops two algorithms this is based on the machine learning and hypothesis testing of NLOS/LOS two separate measurements. The environmental of several indoor experimentally shows our techniques that can distinguish between the LOS/NLOS criteria with an accuracy of around 89%.

For the last few years, there are various approaches have been presented for localizing indoor as well as for utilizing outdoor. Most of the famous localization method measures the radio frequency (RF) signals [11] and Time of Flight

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(ToF) [9], which are the best example used for the GPS system. Due to the short distance and synchronization of inaccurate time of nodes are usually this method cannot be functional in the WSN [1]. On the Backpropagation (BP) networks [2] the error surface is characterized in the system. The BP algorithm has a fixed learning rate measurements are more efficient this is because of over adjustment of the weight it prevents the learning rate of the surface regions.
The signal strengths are determined the mathematical models as well as utilizing the empirical process. The acoustic ToF and RSSI are used to compute the distances between each mobile nodes [3], third reduce the convolution of the usage of an audible frequency system. The RSSI based on the ad hoc network are localized in the WSN system, it can be used to absolute and relative determinations [5]. The more than one base station are down the process of the majority of nodes is taken over only partial roles of localization data.

III. Proposed Methodology

A) Target Action Model

In the co-ordinate plane 2-D Cartesian are consider has a single target movement according to the dynamic process of noise acceleration of hybrid backpropagation

$$\mathbf{x}t = \mathbf{C}\mathbf{x}t-1 + \mathbf{v}t$$

where, constant parameters C models with the state of kinematics, the tracking target state at time t is defined as $\mathbf{x}t = [xt,\ \dot{x}\ t,\ \ yt,\ \dot{y}t]^T$, xt and yt denote the sensor node target position, velocities denotes $\dot{x}$ t and $\dot{y}$t. Gaussian noise of vt with covariance matrix of Q.

B) Sensor Measurement Model

In the co-ordination plane, the two dimensions-Cartesian are deployed sensors randomly bearing the assumption of homogenous process. The fusion center of existing methods is responsible for each sensor by collecting the information and estimation provide to the target nodes. Regarding each sensor of individual knowledge are well-known to the fusion center such as quantization, positioning, and accurate measurements and so on.

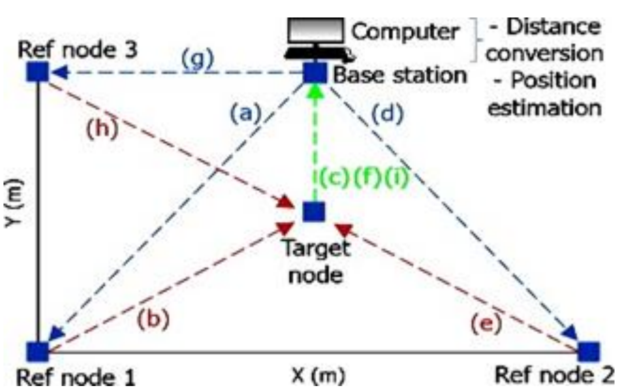

Figure1: Sensor node measurement model

At the each time, only a small numbers of sensors are activated to provide their measurement of quantized and perform the sensing tasks to the fusion centers. The measurement method is given by

$$\theta_i^j = h(x_i) + w_i^j = \tan^{-1}\left(\frac{yi-y^{sj}}{xi-x^{sj}}\right) + w_i^j$$
$$Z_i^j = Q\left(\theta_i^j \bmod 2\Pi\right)$$

where θj, from sensor j the original measurements are i with preservative Gaussian noise **w**j i, whose covariance of parameterized as **P**. The coordination of corresponding sensor j are represented xsj and ysj. The remainder after θj i is divided by 2π is send to the quantizer. Q is a m-bit of uniform quantizer measurement on (−π, π).

Algorithm
Input
Q - Qunatizied measurement of sensor node x[k]
Output
t- Tracking target nodes
Algorithm
Step 1: Estimate the sample co-variance S = ∑Q k=1 $x[k]*X_H[k]$
Step 2: Decompose S using the single value of decomposition:
$R = U\sum V_H$
Step 3: Extract the signal subspace: Us = [u1, u2,…uM] the first M left singular vectors of S
Step 4: Defined : U1 = [u1,….UM-1], u2=[u2,….uM]
Step 5: Perform least square recovery
Ψ = 2π (U2 U1)*(−π, π).

C) HBRB BASED SENSOR NODE SELECTION

The bound ratings are performed to indicate the HBRB selection, and there is no balanced estimation represents to outperform the mobile sensing node. Usually, everyone concerned to achieve the target position. So, here choose a summation of the position rating bound along with each axis and cost function of time to represent T+1

$$C_{T+1} = J^{-1}{}_{t+1}(1, 1) + J^{-1}{}_{t+1}(2, 2)$$

Where, the $J^{-1}{}_{t+1}(1, 1)$ and $J^{-1}{}_{t+1}(2, 2)$ are the bound on the mobile node corresponding to x_{t+1} and y_{t+1} of process. Assume to choose subsets consisting of L^t_s sensors from the threshold of L_s candidates on each tracking node rate at time t, where L^t_s can change over time. Those collective sensors ratings are minimized using the above cost function and it will be activated at the next time t + 1. In this paper, utilize the optimal quantized method to determine the optimal tracking of target sensor nodes.

D) RSS data based tracking nodes

For the individual sensor node BP rating, input are selected as information of RSS data, and the output of coordinates of *x* and *y* taken as mobile sensor. The input I_1 and output O_1 for the BP rating networks are represented as :

$$I_1 = [P_1, P_2, \ldots\ldots, P_n]$$
$$O_1 = [x_m, y_m]$$

Where, Pi is the RSS at BP*i*.

E) Ensemble Backpropagation rate based on hybrid method

Based on the rating backpropagation the sensor networks of the final output **O** is designed as follows:

$$O(I,w) = w_1O_1(I_1) + w_2O_2(I_2)$$

Where, *wi* is the weight of the i^{th} backpropagation rate, which is designed by the individual tracking errors.

$$Wi = (E-e_i)/E$$

Where $E = e_1 + e_2$.

IV. Results and Discussions

The experimental results show that the actual environments, the proposed methods still maintain robust and good results. In this sector, the performance of the proposed techniques is estimated and compared with the existing techniques in term of quantized measure, time complexity and accurate target tracking.

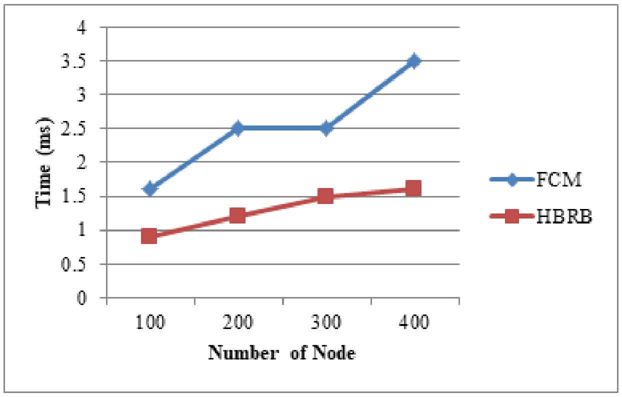

Figure 2: Execution time of existing and proposed techniques

Node Tracking Accuracy

The target node of exactness is depending on accomplishment of a sensor node by manipulating the threshold of the backpropagation rating of the hybrid techniques. The accuracy of the presented and existing algorithm has been illustrated in figure 3.

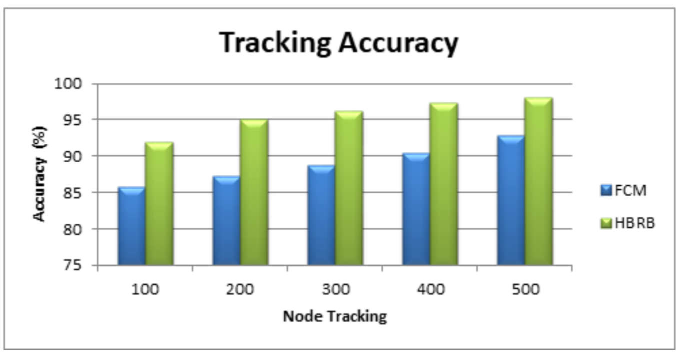

Figure 3: Accuracy of Sensor Node tracking

The above figure 3 has clearly demonstrated that the proposed algorithm has given a higher accuracy than the existing algorithm such as the standard method of FCM and HBRB. From this comparison, the accuracy result proved that the proposed system will provide high accuracy for reaching the target node.

V. Conclusion

Considering, the sensor node selection problem through tracking a single target of sensor networks are dimensional quantized. The one-step lookup process is ahead in posterior HBRB is recursive approximately by using the particle filters that are used to estimate dynamically as well as. Through establishing the HBRB the sensor nodes collectively reduce the cost of the functions while other sensors states remain in the idle stage to save the energy consumptions. The hybrid method supports for both mobility and sensor node to threshold the backpropagation for computing target regions. Compared to our proposed method, with one of the theoretical based on information measurement. Significantly demonstrate the simulation result of improving the optimized performance of our approaches.

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