

COORDINATION OF MOBILE SENSOR FOR TARGET TRACKING BY USING KALMAN FILTER

Y.SUNANDA[1], Y PAVAN KUMAR REDDY[2], DR.K.SHANKAR[3], M.RAVI KISHORE[4]

[1,2,4] *Assistant Professor, Department of Electronics and Communication Engineering*
[3] *Associate Professor, Department of Electronics and Communication Engineering*
[4]*Annamacharya Institute of Technology and Sciences, Rajampet*

[1]*sunanada.bujji@gmail.com,* [2]*ratnasena.reddy@gmail.com,* [3]*shan87.maddy@gmail.com,* [4]*ravi.mvrm@gmail.com*

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ABSTRACT

The target tracking problem is investigated for a tracking system with mobile range sensors. Being different from most previous studies, both additive and multiplicative noises in measurements are taken into consideration. An optimal coordination strategy, including sensor selection and sensor motion is proposed to maximize the tracking accuracy. A wireless sensor network by combining maximum likelihood estimation and Kalman filtering using the distance measurements. The maximum likelihood estimator is used for prelocalization of the target and measurement conversion to remove the measurement nonlinearity. The converted measurement and its associated noise statistics are then used in a standard Kalman filter for recursive update of the target state. In particular, by fully utilizing the properties of objective function, the search space and variables of the original optimization problem can be significantly reduced. Based on this reduction, three algorithms are designed respectively for the following 1) Efficient selection of task sensors 2) Reduction on combinations of task sensors and 3) Efficient search of optimal sensor motion. Applying K-means clustering algorithm in order to make the target tracking process more accurate and efficient by reducing the motion distance of mobile node during data collection.

Keywords: Fisher Information Matrix, Multiplicative Noise, Sensor motion, Sensor Selection, Target Tracking.

1.INTRODUCTION

A Wireless Sensor Network (WSN) of spatially distributed autonomous sensors to monitor physical or environmental conditions such as temperature, sound pressure, etc. and to cooperatively pass their data through the network to a main location. The more modern networks are bi-directional also enabling control of sensor activity. The development of wireless sensor networks was motivated by military applications such as battlefield surveillance. Today such networks are used in many industrial and consumer applications mostly in industrial process monitoring and control machine health monitoring and so on. The WSN is built of nodes from a few to several hundreds or even thousands where each node is connected to one (or sometimes several) sensors.

However in sensor networks hundreds and in the extreme hundreds of thousands of sensors are deployed in a large geographical area. In some cases dropped from airplanes or deployed using artillery shells. Requiring that every node must work in order for the network to operate.

A proposed network with coordination strategy including sensor selection and motion has been proposed for a range-only tracking system with mobile sensors randomly scattered. In this work the concept of tracking accuracy metric which is derived based on the measurement model with both AMN has been used and the search space of each sensor is reduced from a round to a curve. Then considering the movable region of each sensor an algorithm is designed to select the candidate task sensors at each time the step following upon an algorithm for the reduction on the number of sensor combinations.

2.K-means CLUSTERING

K-means clustering is a method of vector quantization originally from signal processing that is popular for cluster analysis in data mining. K-means clustering aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean serving as a prototype of the cluster. This results in a partitioning of the data space into Voronoi cells. The problem is computationally difficult (NP-hard) however there are efficient heuristic algorithms that are commonly employed and converge quickly to a local optimum. These are usually similar to the expectation-maximization algorithm for mixtures of Gaussian distributions via an iterative refinement approach employed by both algorithms. Additionally they both use cluster centers to model the data however k-means clustering tends to find clusters of comparable spatial extent while the expectation-maximization mechanism allows clusters to have different shapes.

3. KALMAN FILTER

Kalman filtering also known as linear quadratic estimation (LQE) is an algorithm that uses a series of measurements observed over time containing noise (random variations) and other inaccuracies and produces estimates of unknown variables that tend to be more precise than those based on a single measurement alone.

More formally the Kalman filter operates recursively on streams of noisy input data to produce a statistically optimal estimate of the underlying system state. The filter is named for Rudolf (Rudy) E. Kálmán one of the primary developers of its theory. The Kalman filter has numerous applications in technology.

A common application is for guidance navigation and to control the vehicles particularly aircraft and spacecraft. Furthermore the Kalman filter is a widely applied concept in time series analysis used in fields such as signal processing and econometrics. The algorithm works in a two-step process.

State Prediction

The state prediction equations is given in (1) and (2)

$$\hat{X}_{k|K-1} = F\hat{X}_{K-1|K-1} \quad (1)$$

$$P_{K|k-1} = FP_{k-1|k-1}F^{T} + GQG^{T} \quad (2)$$

State Estimation

The state estimation equations is given in (3),(4),(5),(6)

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$$S_k = \overline{C}P_k|_{k-1}\overline{C^T} + R_k \quad (3)$$

$$K_k = P_{k|k-1}\overline{C^T}S_k^{-1} \quad (4)$$

$$\hat{X}_{K|k} = \hat{X}_{K|k-1} + K_k(\overline{z_k} - \overline{C}\hat{X}_{k|k-1}) \quad (5)$$

$$P_{K|K} = P_{k|k-1} - K_K S_K K_K^T \quad (6)$$

Where,

$\hat{X}_{K|k-1}$ –Predicted state

$P_{k|k-1}$ – Co-variance of the predicted state

$\hat{X}_{k|k}$ –Estimated state

$P_{k|k}$ – Co-variance of the estimated state

K_K – Kalman gain

$S_{K|k-1}$ – Co-variance of the predicted measurements

In the eqn (1), (2) prediction step the Kalman filter produces estimates of the current state variables along with their uncertainties. Once the outcome of the next measurement (necessarily corrupted with some amount of error including random noise) is observed these estimates (3), (5), (6) are updated using a weighted average with more weight being given to estimate with higher certainty. Equation (4) is kalman gain.

Because of the algorithm's recursive nature, it can run in real time using the present input measurements and the previously calculated state and its uncertainty matrix and no additional past information is required. Extensions and generalizations to the method have also been developed, such as the extended Kalman filter and the unscented Kalman filter which works on nonlinear systems.

4. MODULES

Candidate Task Sensor Selection

Intially it is not necessary to select all Nk sensors that detect the target as candidate task sensors because a number of sensors offer relatively poor measurements and can be excluded. The main idea is as follows, k is strictly monotonically increasing function of gi,k if the angle range of sensor i can cover one of the sensor j and gi,k > gj,k sensor i certainly providess more informatics measurement than sensor j does thus sensor j should be excluded. Suppose Lk sensors are selected as candidate task sensors via Algorithm 1 which produces CM Lk possible combinations. It is notable that usually CM Lk is much smaller than CM Nk even if Lk is slightly smaller than Nk.

Reduction of Sensor Combination

There may be still a large number and further simplification is needed. Clearly if the best localization accuracy associated with combination p = 1, 2. . . CM Lk is smaller than the worst accuracy associated with combination q = 1, 2. . . CM Lk combination p can be excluded.

Optimal Motion Strategy

If there are Ck combinations remained after applying Algorithm 2. For each combination it is necessary to find the corresponding optimal sensor motion thus the global optimal combination and motion of task sensors can be readily obtained by traversing all combinations. Consider combination p = 1, 2. . . Ck. Since the new position of each sensor is determined there are 2M variables that need to be optimized. After comparing the optimal tracking accuracy of all ck combinations the global optimal combination of task sensors and the corresponding motion can be finally determined.

5. TRACKING ALGORITHM

An iterative algorithm is adopted to move sensors for the improvement of tracking accuracy. Simulation results illustrate the efficiency of our proposed strategy. Our proposed coordination strategy can be extended to other cases. For the case of bearing-only sensors with AN and the FIM-based metric is also a function of sensor–target distance, angles and shorter distance leads to a better tracking performance which is in the same mathematical form of the range-only sensors we considered. Therefore our proposed coordination strategy can be easily extended to the case of bearing-only sensors.

6. SYSTEM ARCHITECTURE

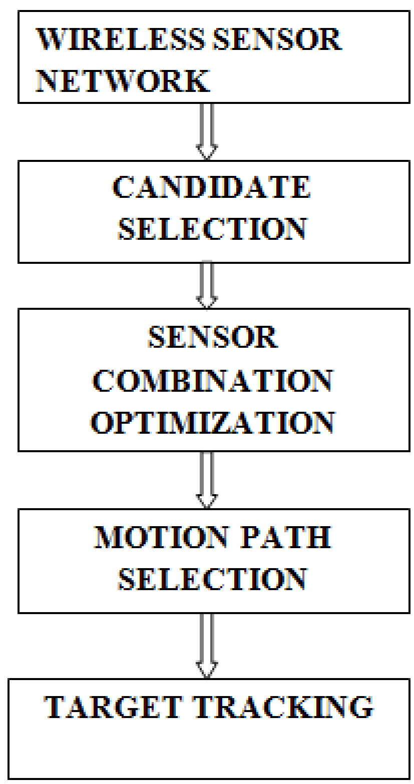

Figure 1 system Architecture

Figure 1 shows the system architecture, wireless sensor network consist of number nodes in built them and also link between one node to another node. Target tracking is nothing but to process

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noisy sensor measurements received from one (or) more sensors and estimate the state of an object.

7. MAXIMUM LIKELIHOOD ESTIMATOR

Maximum-Likelihood Estimation (MLE) is a method of estimating the parameters of a statistical model. When applied to data set and given a statistical model maximum likelihood estimator estimates the model's parameters.

The method of maximum likelihood corresponds to many well-known estimation methods in statistics. For example, one may be interested in the heights of adult female penguins but be unable to measure the height of every single penguin in a population due to cost or time constraints. Assuming that the heights are normally (Gaussian) distributed with some unknown mean and variance. The mean and variance can be estimated with MLE by knowing the heights of some samples of the overall population. MLE would accomplish this by taking the mean and variance as parameters and finding particular parametric values that makes the observed results the most probable one.

8. ITERATIVE ALGORITHM

In this the problems of finding the root of an equation an iterative method uses an initial guess to generate successive approximations to a solution. In contrast direct methods attempt to solve the problem by a finite sequence of operations. In the absence of rounding errors direct methods would deliver an exact solution. Iterative methods are the only choice for nonlinear equations. However iterative methods are often useful even for linear problems involving a large number of variables where direct methods would be prohibitively expensive even with the best available computing power.

9. SIMULATION RESULTS AND DISCUSSION

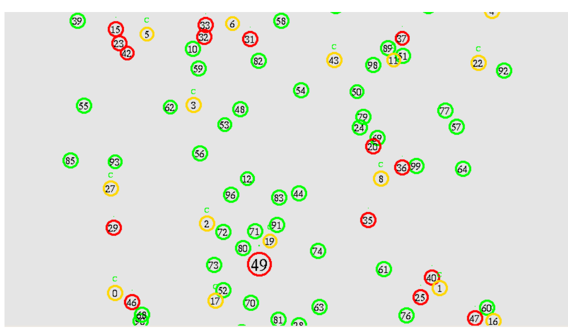

Figure 2 CTSS and MMCR Algorithm Implemented Output

Figure 2 shows the CTS and MMCR implemented output.and also use the node to node two way communication,and also use the AODV routing protocol.and then forty nineth node is a sink node and also sink node is a link between all other nodes and sends the constant bit rate.

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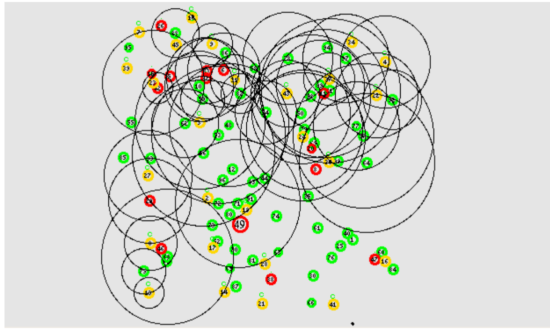

Figure 3 Simulated Output of Broad Casting between One Node To Another Node

Figure 3 shows the broadcasting communication between one node to another node,sends the link between one node to another node for eg.(12 32) and also send the constant bit rates.

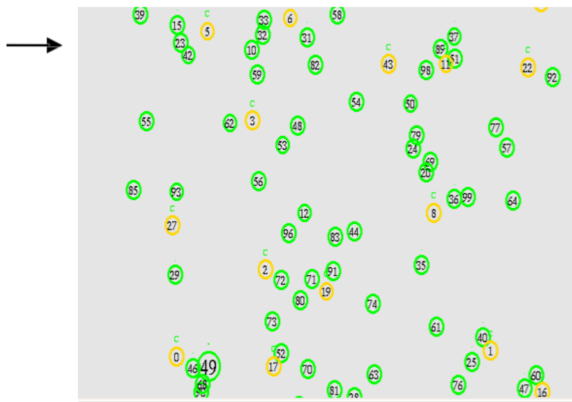

Figure 4 Simulated Output of Sensor Motion Iterative Algorithm

Figure 4 shows the implemented the sensor motion iterative algorithm. The sink node start to moved by region by region.in order to start the sink node sends the first link between neighbour nodes.AODV protocol sent the one node to another node.and finally collects the data from all other nodes.

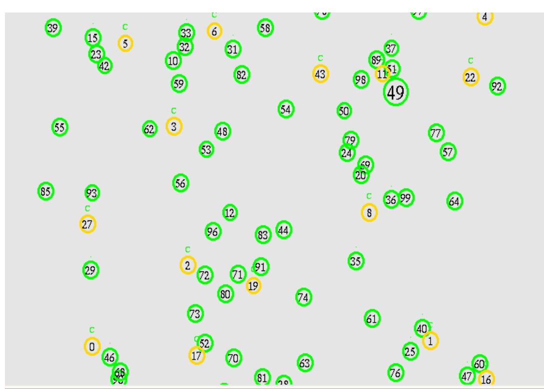

Figure 5 Simulated Outputs of Path Identication and Optimization

Figure 5 shows the simulated output for path identification and optimization output.the sink node identify the shortest path and also optimize the sensor nodes.this is very useful for target tracking problem identification.

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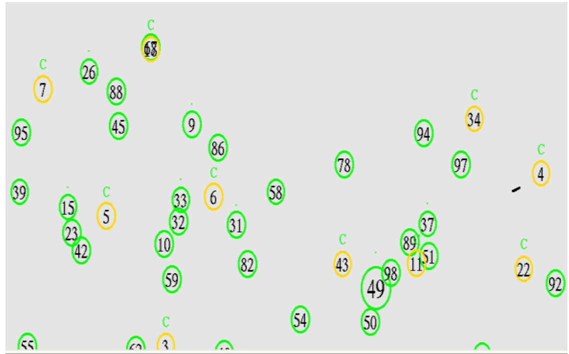

Figure 6 Sink Node Sends the Constant Bit Rate and Collects the Data From Nodes

Figure 6 shows the sink node sends the constant bit rate and collects efficient data from all other nodes.delay is reduced and also all nodes are energy efficient nodes.in future the is accurately reduced,and also use the k-means clustering is apply the output is efficient one.

10. CONCLUSION

A coordination strategy including sensor selection and motion has been proposed for a range-only tracking system with mobile sensors randomly scattered. According to the properties of the tracking accuracy metric which is derived based on the measurement model with both AMN the search space of each sensor is reduced from a round to a curve. Then considering the movable region of each sensor an algorithm is designed to select the candidate task sensors at each time step following upon an algorithm for the reduction on the number of sensor combinations. They both simplify the process of sensor selection in a great deal. An iterative algorithm is adopted to move sensors for the improvement of tracking accuracy. For the case of bearing-only sensors with AN the FIM-based metric is also a function of sensor–target distance and angles and a shorter distance leads to a better tracking performance which is in the same mathematical form of the range-only sensors are considered. Therefore the proposed coordination strategy can be easily extended to the case of bearing-only sensors.

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