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Application of covariance cross in distributed sensor network positioning

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ABSTRACT

Node localization accuracy in many applications in a distributed sensor network plays a vital role. Currently positioning method is more concerned mainly include TDOA and RSS. These two methods are non-independent and positioning accuracy susceptible to noise. If using the traditional manner fusion Kalman filter data, you can reduce the estimation error. But assumes zero covariance between data, so the results are not conservative and reliable. This article will cross covariance data fusion algorithm is applied to such problems, namely in the Poisson distribution and uniform distribution of node localization process distributed sensor network to be simulated. The results show that the algorithm is more reliable crosscovariance and improves positioning accuracy, ideal for distributed sensor networks.

KEYWORDS

Distributed sensors; Covariance cross; Received signal strength.

INTRODUCTION

Distributed Sensor Network (DSN) by way of random deployment, a large number of tiny sensors to monitor the actual launch intensive environments, the connection between the sensor nodes through the wireless channel, and according to their location and energy equipment, selforganizing networks. As the number of the network topology of sensor nodes, the position and the dynamic adjustment of the ambient condition change. DSN random deployment, selforganization, adaptation to the environment and other characteristics make it in environmental monitoring, theater monitoring, medical monitoring, inventory management, intelligent home control and management, have a high value. As the number of nodes increases the sensor, positioned and configured for them to become more complex and difficult.

The node localization features in many applications in both DSN plays a vital role. One solution we can take is to giveeach node is equipped with GPS, in order to obtain absolute position information, but will lead to huge costs and energy consumption. And put more reference nodes or increase computing centers to perform data processing (Computation Center) data transfer amount would impose an unreasonable burden on the DSN redundant. In this paper, using the method of distributed data fusion technology to improve the DSN node localization accuracy.

Wireless location technologies include arrival time positioning (TOA), time difference of arrival location (TDOA), and angle of arrival positioning (AOA) and received signal strength positioning (RSS) technology. TOA positioning requirements of the received signal node that signals the beginning of the transmission time, and requires a system with precise clock synchronization. AOA positioning requirements of expensive array antennas set up, increasing the cost of the receiver. At present, more attention is TDOA and RSS positioning technology, but their accuracy susceptible to noise. In this paper, cross-covariance method (CI), to be converged on TDOA and RSS measurement data to improve positioning accuracy DSN.

DSN ARCHITECTURE

In the DSN generally assume a small amount to ascertain their location coordinates of the reference node (reference node), the remaining number of nodes are unknown position themselves ordinary nodes (general node). Between nodes need to have the ability to pass information to each other. All nodes through its neighboring nodes, using triangulation to estimate the location information. In the centralized positioning, DSN has a central control station, i.e., computing center (CC), CC establishment of a database for each reference node according to the relation obtained by the signal strength measurement and the reference position of the node. The remaining common nodes of the detected radio signal strength reference node sent to CC, CC and then by querying the database to determine the position of the ordinary node. Centralized positioning and the need to support a large number of reference nodes CC.

Just set a small amount distributed positioning reference node. The short distance to thereference node can calculate its position based on the location of the reference node; distance with the reference node has been positioned by a plurality of adjacent nodes to determine their location. Therefore, this positioning has good scalability, but the multi-level node localization error of positioning errors is associated with the previous. When this association cannot ascertain the extent of the time, CI fusion Kalman filtering technique than traditional advantages. Localization of the way the structure shown in Figure 1.

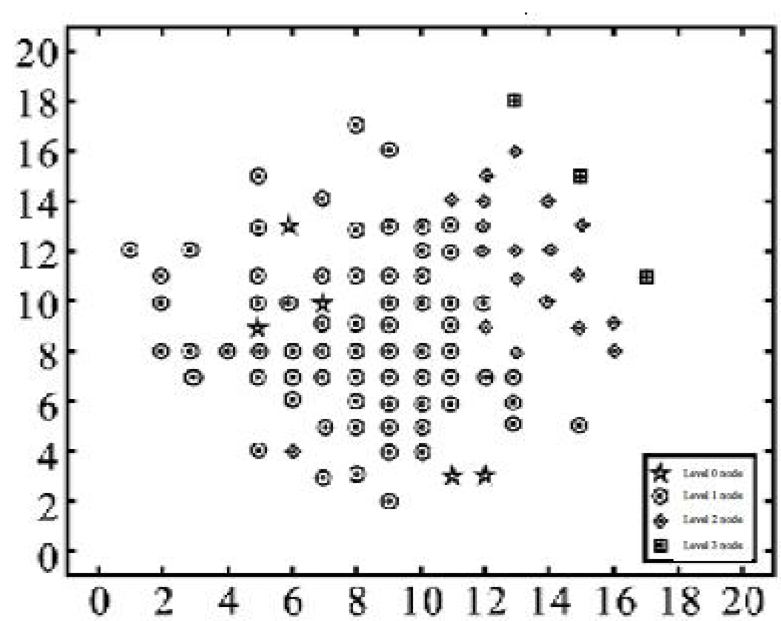


Figure 1 : DSN positioning probe structure

TDOA location

TDOA technology required to locate nodes by calculating the number of different transmission time difference positioned nodes to obtain location information. Expression of the received signal is:

$$y_i(t) = a_i s(t-\tau_i) + e_i(t),\ i = 1, 2, \ldots, n \tag{1}$$

Among them, the i-th node has positioned coordinates (xi, yi). Required to transmit the positioning coordinates for the nodes (x, y), it is the i-th node and the j-th node of the path difference is:

$$d_{i,j} = v(\tau_i - \tau_j) + \varepsilon_{TDOA},\ 1 \le i \le j \le n \tag{2}$$

Where v is the propagation speed of the signal. The last parameter is TDOA positioning error, subject to zero-mean Gaussian distribution.

RSS positioning

RSS sent out positioning based on the received power of the radio signal to be a positioning node determining the relative position information. Send and receive signals power relationship by Fu Lizi (Friis) transmission formulas derived,

$$\frac{P_r}{P_t} = \frac{A_{er} A_{et}}{r^2 \lambda^2} \tag{3}$$

Where, Pr is the received power (W);
Pt is the transmit power (W);
Aer for effective receiving antenna aperture (m2);
Aet for effective transmitting antenna aperture (m2);
r is the distance (m) between the transmitting and receiving antennas.
When transmitting antenna directivity, etc., with the following expression:

$$P_r = \frac{A_t A_{et}}{4\pi r^2} \tag{4}$$

The combination of the constant value of the parameter K, then the following expression:

$$P_r = \bar{P_t}\ K\ r^2 \tag{5}$$

Thus has the following expression:

$$r = \sqrt{\frac{P_r}{P_t} K + \varepsilon_{RSS}} \tag{6}$$

The above expression, the last one is RSS positioning error; obey the Gaussian distribution with zero mean. Equation (6) indicates that the distance measurement accuracy depends on the power of RSS measurement accuracy.

COVARIANCE INTERSECTION ALGORITHM (CI)

CI algorithm is unknown relevance to the integration of data from the Julier and Uhlman method proposed. If two random variables are not relevant, we can use the fusion Kalman gain so that the estimation error is smaller than or equal to the integration error in any one of the previous estimate. But Kalman filter for relevance unknown data is powerless. In this case, the use of CI data fusion algorithms can solve this problem.

Suppose two state estimation of the mean and variance are {a, Paa}, {b, Pbb}, integration result is noted as {c, Pcc}. Typically an unbiased estimate of c is a linear combination of a and b, as follows:

$$c = K_1 a + K_2 b \tag{7}$$

When Pab = 0,

$$\begin{cases} K_1 = P_{bb}(P_{aa} + P_{bb})^{-1} \\ K_2 = P_{aa}(P_{aa} + P_{bb})^{-1} \end{cases} \tag{8}$$

Integration of results:

$$\begin{cases} P_{cc} = (P_{aa}{}^{-1} + P_{bb}{}^{-1})^{-1} \\ c = K_1 a + K_2 b \end{cases} \tag{9}$$

When Pab ≠ 0, the use BPaa, BPbb, BPcc respectively Paa, Pbb, Pcc corresponding covariance ellipse area. Paa covariance ellipse constituted by the point where q(x,y) of the collection. k is a constant.

If Pab unknown,

$$\begin{cases} K_1 = wP_{cc}P_{aa}{}^{-1} \\ K_2 = (1-w)P_{aa}P_{cc}P_{bb}{}^{-1} \end{cases} \tag{10}$$

Integration of results:

$$\begin{cases} P_{cc} = (wP_{aa}{}^{-1} + (1-w)P_{bb}{}^{-1})^{-1} \\ c = K_1 a + K_2 b \end{cases} \tag{11}$$

Where w is the value of different options that can be used on most different meanings, such as: making Pcc trace take minimum. At this time, $B_{P_{cc}} \supset B_{P_{aa}} \cap B_{P_{bb}}$

If Pab known,

$$P_{cc} = P_{aa}{}^{-1} + (P_{aa}{}^{-1}P_{ab} - 1)(P_{bb} - P_{ab}{}^{T}P_{aa}{}^{-1}P_{ab})^{-1}\ (P_{ab}{}^{T}P_{aa}{}^{-1} - 1) \tag{12}$$

At this time, $B_{P_{cc}} \subset B_{P_{aa}} \bigcap B_{P_{bb}}$

Figure 2 shows the data related to the degree of integration of the unknown covariance ellipse. w Select 0.3 and 0.7 respectively. Seen from Figure 2, BPcc contains part BPaa and BPbb the intersection.

We need to be fused and T DOA RSS positioning data, to produce a new estimate of the data. The use of Kalman filtering, correlation needs to be set to zero. This independence assumption that the filtering results transitional confident, non-conservative. Therefore, we use CI algorithms.

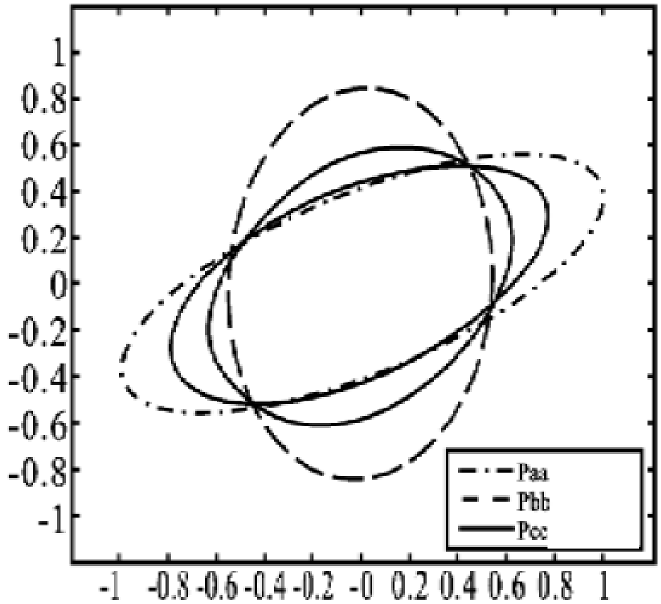


Figure 2 : Covariance ellipse

SIMULATION PROCESS

Simulation model

$20m^2$ randomly put in 100 ordinary nodes and three reference nodes. Node in turn chooses the Poisson distribution and uniform distribution to be simulated. Node transmission radius of 5m. In addition to relying on the reference node localization ordinary nodes out of the first round, each remaining node needs to find at least three have been integrated to determine its own location positioning node (trigonometry). TDOA standard deviation of the noise of the transmission range is set to 3%, i.e. 0.15m. RSS is set to the standard deviation of the noise of the transmission range of 5%, namely 0.25m. Our simulation results 100 independent averaged.

First select a node needs to locate within the communication range of the nodes has been located; the measurement range is estimated to obtain information from the other side, and the integration of TDOA and RSS data. Then through the three or more measurements of the neighbors has been positioned, their position is estimated. Finally, their location is broadcast to neighboring nodes, updates DSN structure.

Simulation results and analysis

Figure 3 and Figure 4 for an independent experiment, respectively, using the Poisson distribution and levels of node localization process DSN evenly distributed. Among them, taking Poisson distribution with mean 10, and thus the node distribution is more evenly distributed and more concentrated toward the center. The process of generating a random number may be formed of the same coordinates ordinary nodes, and the latter may cause random put to a common reference node coincides with the position of the node. Thus the total number of nodes shown in the figure may be less than 103.

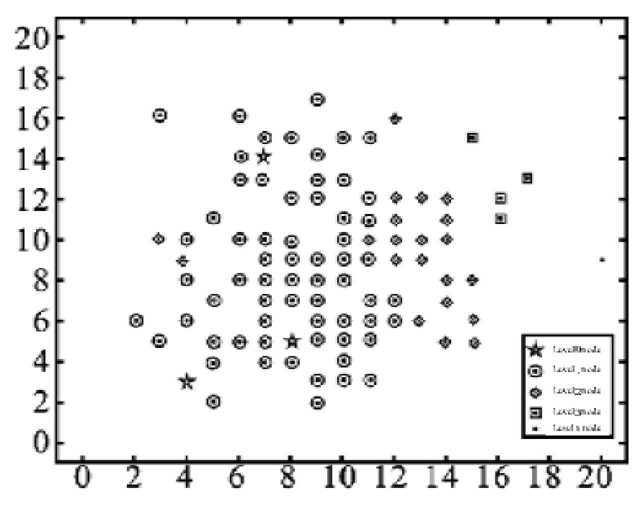


Figure 3 : Poisson distribution DSN positioning

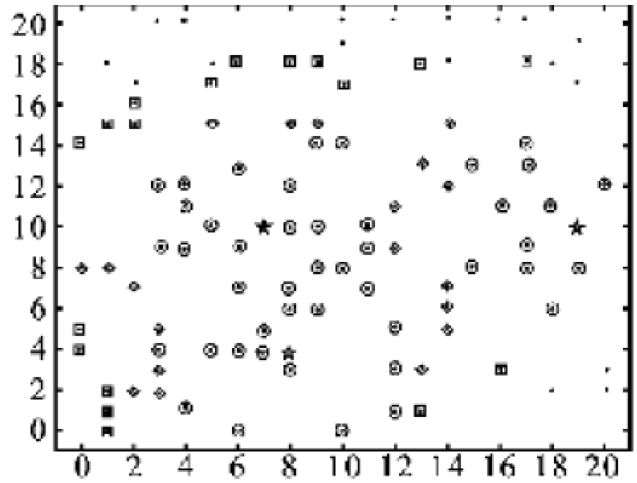
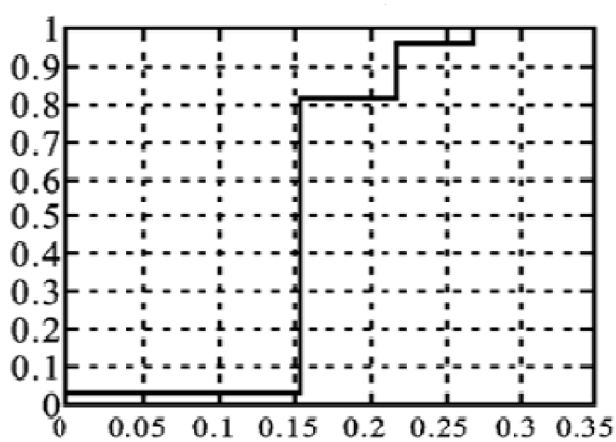
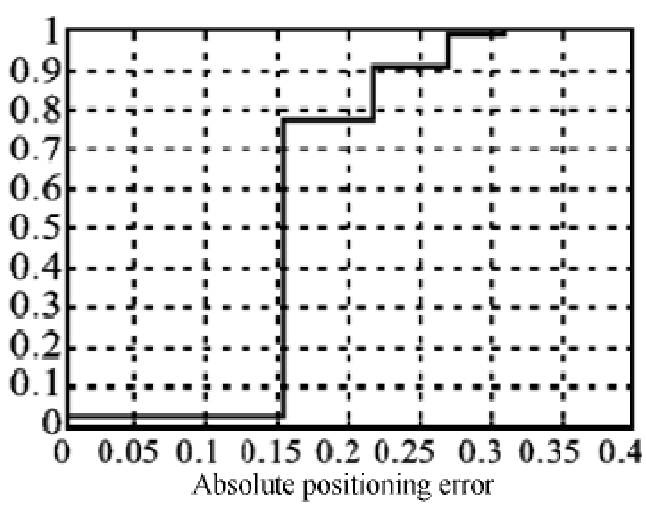


Figure 4 : Evenly distributed DSN positioning

Figure 5 shows the absolute positioning error for the Poisson distribution nodes cumulative distribution function. The figure shows increases in the positioning of the nodes are positioned adjacent the required number of nodes has been located; it will lead to positioning errors increases. 5 has been positioned by the positioning neighbor nodes (Figure 5a), more than 90% of the position error is less than the node 0.22m (w take 0.9). Figure 6 illustrates when parameter settings are the same, the positioning error is higher than the positioning error uniformly distributed Poisson distribution.

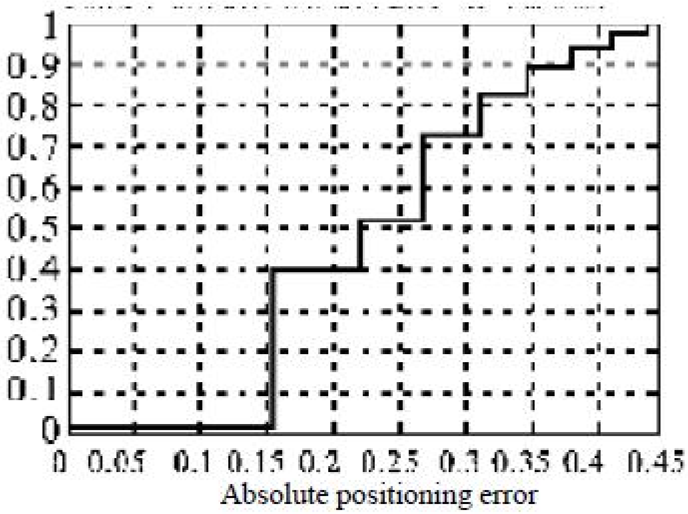


(a) 5 reference critical points

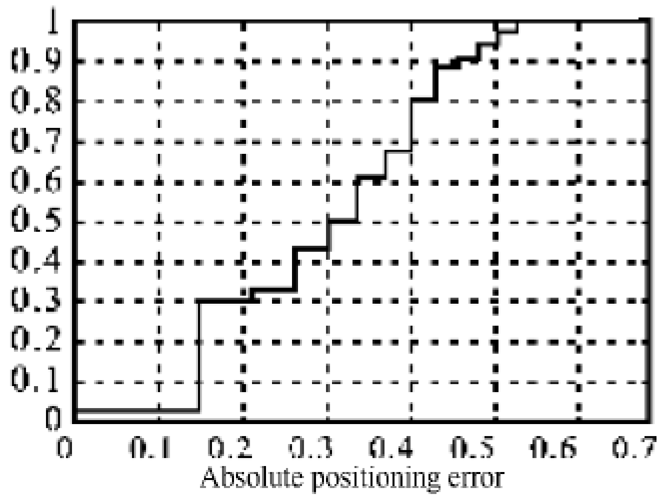


(b) 10 reference critical points

Figure 5 : Under the cumulative distribution function of the Poisson distribution DSN node localization errors



(c) 5 reference critical points



(d) 10 reference critical points

Figure 6 : Under the cumulative distribution function of a uniform distribution DSN node localization errors

Simulation results show that after the first two position, most of the node locations have been identified. After the first six positioning, all nodes have completed positioning.

CONCLUSION

In this paper, cross-covariance algorithm, the DSN distance measurement data to be fused. Under T DOA and RSS relevance is unknown, CI Kalman filter algorithm is more conservative compared to the reliable and improve the positioning accuracy. DSN positioning accuracy of the Poisson distribution is slightly better than the uniform distribution. Most ordinary node localization can be done the first two rounds. CI algorithm is more suitable for DSN positioning system.

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