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Research on Error Revisal of Sensor Networks Based on Genetic Algorithm

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Abstract: In the modern information system, the network composed by multiple sensors could obtain information in a larger scope and fetch data more effective and accurate than a single sensor. Improve the accuracy of the sensor network and correct the systematic errors of sensor are the major problems for organizing the sensor network. On the basis of analyzing the system error and random error of sensor networks, transform the revisal of system error into a nonlinear optimization problem and then establish registration error objective function and adopt genetic algorithm for optimal solution. The result of simulation shows that without prior knowledge, the accuracy of the sensor network after the registration has been greatly improved.

Key words: Sensor networks, error analysis, genetic algorithm, registration

INTRODUCTION

The sensor networks of large scale and randomly scattered mode have been widely used in military defense, environmental monitoring, health care, industrial production control, disaster relief and other important area. In this mode, on the one hand node portfolio management should be carried out effectively to achieve good coverage under the premise of ensuring the network reliability (Lee and Lee, 2003); on the other hand, how to make sensors measurement error correction registration to improve the measuring accuracy of the network, is one of the most important issues of the random distribution mode sensor network (Navarro and Yatesa, 2002). In this paper, we design a network error correction method based on genetic algorithm, which can make effective error calibration through simulation analysis on the premise of the unknown priori knowledge.

MEASUREMENT ERROR ANALYSIS

Sensor network is composed of a network of sensor nodes. Sensor nodes have the function of the end node and routing: on the other hand, they can implement the data acquisition and processing; on the other hand, they can make a comprehensive and fusion processing of data collected by them and send by other nodes and forward route to the gateway node. Gateway node number is limited and often uses a variety of ways to communication with the outside world (Papadinitriou, 2004).

In terms of observation data for a single sensor, the measurement accuracy of error distribution characteristics are always worse. Sensor measurement errors include system error and random error. In sensor networks, we can use the target redundant information for data fusion to improve positioning accuracy and error distribution characteristics (Zhang *et al*., 2008). However, the system error of each sensor is basically constant, although it can't be solved by the method of data fusion but can be eliminated using error registration.

Systematic errors: In general, the system error of a single sensor is constant and independent. In sensor networks, if the sensor measurement data are accurate, then the measurement results are completely the same for the observation area of the same location of each sensor. But due to the presence of random error, we can only make observations on the same position as close to as possible and can reduce uncertainty and improve the measurement precision and quality through more complementary information between nodes. But in the actual using process of sensor networks, we find that multiple nodes fusion effect did not reach that target and sometimes even worse than a single sensor measurement result (Feng, 2010), an important reason for this phenomenon is that registration error problem hasn’t been resolved. The purpose of error registration is to estimate the system error of each sensor based on each sensor measurements on the same target.

Random errors: In sensor networks, there must be more than two detection nodes implement data measurements on the overlapping area and then we can apply the observations of redundant data to conduct data fusion, so as to improve the error distribution characteristics and measuring precision. The basic for Multi-source data

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fusion is the quantitative evaluation of the accuracy of source data characteristics; the optimal method is through the real-time calculation of the precision of each link point, to determine the weight value of weighted fusion. In order to satisfy the requirements for point-by-point integration under high data rate condition, we can adopt fusion method based on intersection angle to reduce the random error (Wang and Guo, 2006).

SYSTEMATIC ERRORS REGISTRATION BASED ON GENETIC ALGORITHMS

This section takes the measurement of the sensor network of the target azimuth information as an example, by establishing error registration model function, converted an error registration problem into a nonlinear optimization problem and a genetic algorithm is used to resolve the model.

Construction of Error registration objective function: The sensor used for probing location information is relatively simple and typical direction sensor, the technology is relatively mature and the cost is low. The measurement result is one dimensional data, after the networking, data fusion processing through each node direction finding data could realize target location and tracking for continuous cover detection area, which has wide application value in the field of military defense and aerospace technology (Gao and Shan, 2007).

Assuming three sensors A, B and C, adopt the method of projection to convert the position and measuring parameters of different sensors to the same cartesian plane and the coordinates are (x_A, y_A), (x_B, y_B) and (x_C, y_C) and, respectively, as shown in Fig. 1.

In the observation time t, the target measuring data of the three sensors are $\theta_A(t)$, $\theta_B(t)$ and $\theta_C(t)$, respectively; system error is indicated by $\lambda\{\Delta\theta_A, \Delta\theta_B, \Delta\theta_C\}$. According to the geometrical relationship of Fig. 2, after the system error correction of each sensor, the target location measurement results (X (t), Y (t)) are shown in Eq. 1-3:

$$\begin{cases} X(t) = \dfrac{y_A - y_B + x_B ctg(\theta_A(t) + \Delta\theta_A) - x_A ctg\ (\theta_B(t) + \Delta\theta_B}{ctg(\theta_B(t) + \Delta\theta_B) - ctg(\theta_A(t) + \Delta\theta_A)} \\ Y(t) = \dfrac{[y_A ctg(\theta_B(t) + \Delta\theta_B) - y_B ctg(\theta_A(t) + \Delta\theta_A) + (x_B - y_C + x_C ctg(\theta_B(t) + \Delta\theta_B) \bullet ctg\ (\theta_A(t) + \Delta\theta_B)]}{ctg(\theta_B(t) + \Delta\theta_B) - ctg(\theta_A(t) + \Delta\theta_A)} \end{cases} \quad (1)$$

$$\begin{cases} X(t) = \dfrac{y_B - y_C + x_C ctg(\theta_B(t) + \Delta\theta_B) - x_A ctg\ (\theta_C(t) + \Delta\theta_C}{ctg(\theta_C(t) + \Delta\theta_C) - ctg(\theta_B(t) + \Delta\theta_B)} \\ Y(t) = \dfrac{[y_A ctg(\theta_C(t) + \Delta\theta_C) - y_C ctg(\theta_B(t) + \Delta\theta_B) + (x_C - x_B) ctg(\theta_C(t) + \Delta\theta_C) \bullet ctg(\theta_B(t) + \Delta\theta_B)]}{ctg(\theta_C(t) + \Delta\theta_C) - ctg(\theta_B(t) + \Delta\theta_B)} \end{cases} \quad (2)$$

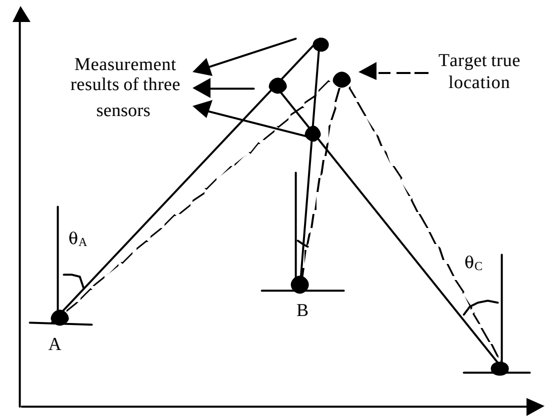

Fig. 1: Geometry relationship of error registration

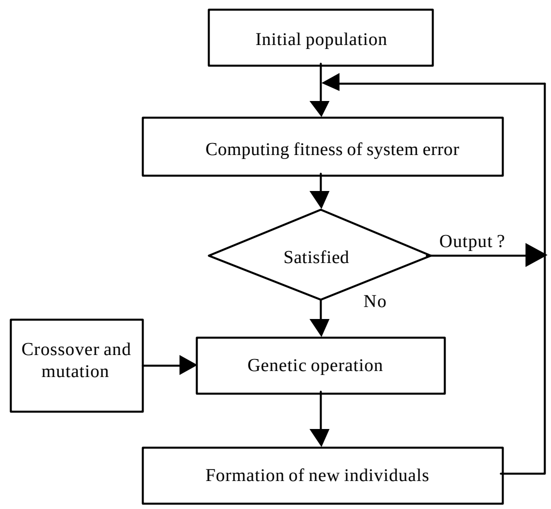

Fig. 2: Algorithm process of sensor network error registration based on genetic algorithm

$$\begin{cases} X(t) = \dfrac{y_C - y_A + x_A ctg(\theta_C(t) + \Delta\theta_C) - x_C ctg\ (\theta_A(t) + \Delta\theta_A}{ctg(\theta_C(t) + \Delta\theta_C) - ctg(\theta_B(t) + \Delta\theta_B)} \\ Y(t) = \dfrac{[y_A ctg(\theta_A(t) + \Delta\theta_A) - y_A ctg(\theta_C(t) + \Delta\theta_C) + (x_A - x_C) ctg(\theta_A(t) + \Delta\theta_A) \bullet ctg(\theta_C(t) + \Delta\theta_C)]}{ctg(\theta_A(t) + \Delta\theta_A) - ctg(\theta_C(t) + \Delta\theta_B)} \end{cases} \quad (3)$$

In the case of ignoring the random error, all measurements should be as close as possible; that means the area of the triangle consist by the three measurement results points is the smallest. According to the theory of plane geometry trigonometry:

$$S = \sqrt{p(p-a)(p-b)(p-c)}$$

$$p = \frac{1}{2}(a+b+c)$$

The area of the triangle is represented as in Eq. 4:

$$S(t) = \frac{[y_A ctg(\theta_A(t)+\Delta\theta_A) - y_B ctg(\theta_B(t)+\Delta\theta_B) + y_C ctg(\theta_C(t)+\Delta\theta_C)](x_A + x_B - x_C)}{[ctg(\theta_A(t)+\Delta\theta_A) - ctg(\theta_C(t)+\Delta\theta_C)] \bullet [ctg(\theta_C(t)+\Delta\theta_C) - ctg(\theta_B(t)+\Delta\theta_B)]} \quad (4)$$

As an objective function of the nonlinear equations, Eq. 4 indicates the goal is for each sensor registrationis that looking for a set of system error values, which make all the measurements points after the registration overlap as much as possible. A set of suitable λ should be sovled, which make the smallest D (t). For the measurement data of n times, a set of λ in a certain range are needed, which make the smallest value of the Eq. 5:

$$B = \sum_{1}^{n} S(t) \quad (5)$$

Processes and structures of genetic algorithms: The algorithm process of Sensor network error registration based on genetic algorithm is shown in Fig. 2.

Step one, determines the length of the chromosome coding according to the system error range and randomly generate n group system errors as the initial populations.

Assuming the maximum measuring error is A (the average value is not less than 3 times of measurement precision), the sign bit is the most significant bit, then the coding accuracy is A/215=3A×10-4 which is far less than the error registration accuracy. Adopting random sequence generate initial solutiong group of system error {b1, b2_Cb3……bn}, bi Bi is is a set of system error codes, n is the number of initial population.

Step two, compute the fitness value of system error of each group, determine the selected probability of system error of each group according to the fitness and sort the fitness value.

Fitness presents the character of the individual; the higher fitness indicates the estimate value of System error value is closer to the true value of the error. The fitness function is shown in Eq. 6; the individual fitness function can be expressed as follows. Larger G (b_i) indicates the smaller area Constituted by two direction line intersection point, which means the smaller registration error:

$$G(b_i) = \frac{1}{\sum_{1}^{i} S(t)} \quad (6)$$

Step three, according to the sorting result, using selection, crossover and mutation operations for updating the group to form the new generation groups.

Selection takes fitness selection as principles and chooses system error estimation of larger fitness to pass on to the next generation directly and then eliminate system error estimation of poor fitness. The selected probability is calculated by the individual fitness in this paper, the probability of the ith individuals being selected to participate in the next generation populations is shows as in Eq. 7, n is the number of the entire individual:

$$Q(b_i) = \frac{\sum_{1}^{i} G(b_k)}{\sum_{1}^{n} G(b_j)} \quad (7)$$

In order to guarantee the convergence of genetic algorithm, ensure the best individual is not broken and can be copied to the next generation, we employ the optimal preservation strategy and replace the individual of worst fitness by the individual of best fitness and then highest fitness can be saved to the populations of next generation.

Variation happens among individuals after the intersection, we make mutation operation to all the individual genes using probability pm, generate 0, 1 randomly assigned to the genes and generate the offsprings.

Step four, stop criterion and adopt the combined method of ruled genetic genetation and individual fitness judging as the termination condition. When genetic genetation is greater than a set value or the change of fitness function value is very small, end of the operation.

SIMULATING CACULATION

Assume that the coordinates of the sensor A, B and C are (24.5-8.9 km), (-5.1-6.3 km) and (-37.2-15.4 km), respectively. Added noise with Gauss distribution of the variance is 0.5 to the measurement results, the target point is (84.81-5.1 km) and the destination is (245.7-90.5 km). Sampling 250 times, the initial population is 800, iterative 4000 times, crossover probability is 0.6 and mutation probability is 0.3, the registration results as shown in Table 1.

The result of Table1 shows that the error registration method based on genetic algorithm can accurately estimate the system errors of each sensor and can make real-time error correction in measuring sensor network data.

Table 1: Comparisonof the algorithm estimate results and actual measurement result

Sensors	Estimate results	Measurement result	Error
Sensor A direction /(°)	0.343	0.382	-0.039
Sensor B direction /(°)	0.375	0.442	-0.067
Sensor C direction /(°)	0.066	0.123	-0.057

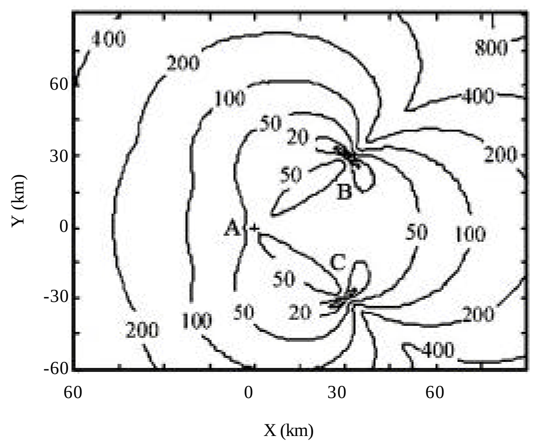

Fig. 3: Error contour line before the registration

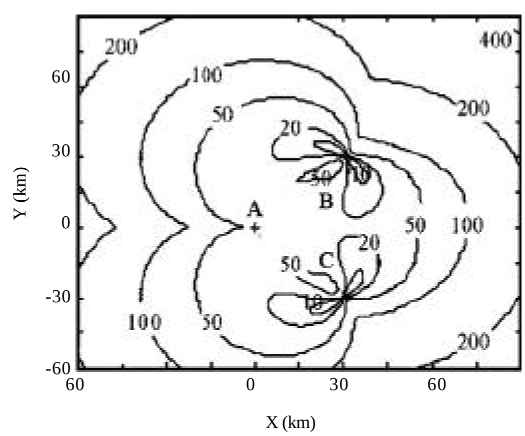

Fig. 4: Error contour line after the registration

Make simulation calculation to distribution characteristics of the errors respectively, the contour map of the errors is shown in Fig. 3 and 4.

Obviously, the error distribution characteristics after registration are greatly improved. The error gradient near A station decreases obviously; the resolution error of the middle position on station C attachment B decreases obviously; there are obvious decreasing trend for the positioning error of the whole area. The error distribution areas of 100 m increase, the fusion data precision increase 29% than the prior error correction.

CONCLUSION

In this study, we design a network error correction method based on genetic algorithm, which can make effective error calibration through simulation analysis on the premise of the unknown priori knowledge. The result of simulation shows that without prior knowledge, the accuracy of the sensor network after the registration has been greatly improved. The method has less restrictive conditions in engineering application, makes higher error estimation precision and is suitable for large scale sensor network applications.

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