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Using Neural Network with Gradient Descent Adaptive Learning Rate Training Algorithm for Geometric Dilution of Precision Approximation

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Abstract—*Thegeometric dilution of precision is widely used as criterion for selecting the best set of the measurement devices. Some methods had been proposed to find the value of theGeometric Dilution of Precision (GDOP), such as using inverse matrix to solve the linear equation.But it takes a large amount of computing to find the optimal solution. In this paper, we proposed a method which use neural network with gradient descent adaptive learning rate training algorithm to approximate the value of GDOP. By the simulation results, it is suggested to combine the service base station with three others to estimate the position of mobile station.This will significantly reduce the computational complexity.*

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I. Introduction

In recent years, mobile positioning is an important issue in wireless communication. There are a lot of methods to locate the mobile station (MS) such as time of arrival (TOA), angle of arrival (AOA), time difference of arrival (TDOA), and signal strength (SS).

TOA located the MS position by measuring the signal arrival time, the signal be send from the base station (BS) to the MS, and the signal include the time information. When MS received the signal from the BS, it can compute the transmission time between the BS and the MS[1]. Using the transmission time gets the measuring distant. In two dimension environments, we need a least three BS to estimate the location of the MS[2]. There are many ways to locate the MS position in wireless communication system, it can be generally divided into two major categories – handset-based methods and network-based methods. The advantages of handset-based methods are higher global converge rate and lower position error than the network-based methods. But the handset-based methods are more expensive because of device requirements and overall system technology integration. The global positioning system (GPS)[3], [4]is a handset-based methods and it can provide the user's location, relative speed and the time information. When equipped the GPS receiver, the handset-based methods must to modify the mobile device's function to estimate its position. The network-based methods depend on the signal measurement between the MS and the BS in the wireless communication system. The network-based methods have lower system complexity than thehandset-based methods, and it can be used in the situation that the signals ofGPScannot be detected, such as in an indoor environments or the basement.The wireless sensor networks(WSN)is a network-based method which has been developed into many applications, such as environments sensing and moving measuring. It is important to get the location of the sensor in the network positioning system, and that is the positioning problem.

Geometric dilution of precision (GDOP) is widely used for increasing the positioning accuracy. GDOP was first proposed to find the best satellite set with the higher locating accuracy in the GPS [5],[6].

In this paper, we applied the GDOP to both handset-based methods and network-based methods. The concept was originally applied for selecting the best satellite set, having the lowliest positioning error in the three-dimensional environment. When choose the set which has the smallest value of the GDOP,we can have higher position accuracy and reduce the influence of the bad geometric distribution. In cellular communication system, selecting appropriate BS set to estimate the MS location can greatly improve the positioning accuracy.

Since the MS will always communicate with the service BS, we can always select the service BS from the seven BSs into the BS set, and combine the others three BSs to form the different BS set, and the number of the BS set will reduce from 35 to 20. By estimating the value of all the different BS set, we can choose the best BS set having the smallest value of the GDOP. The proposed method can be used for GDOP approximation, GPS, WSN, and wireless communication system.

II. Geometric Dilution Of Precision

The Geometric dilution of precision is the criterion for selecting the best BS set and has higher positioning accuracy with better geometric distribution. To improve the positioning accuracy, we should minimize the value of GDOP [7]. In the three-devotional environment, the distant between the satellite and the user can be expressed as

$$r_i = \sqrt{(x-X_i)^2 + (y-Y_i)^2 + (z-Z_i)^2} + c \cdot t_b + v_{ri} \qquad (1)$$

where $(x, y, z)$and (X_i, Y_i, Z_i) are the user's location and the position of satellite$i$, c is the speed of light, $t_b$is the time offset, and v_{ri} is pseudo-range measurements noise. Equation (1) can be represented withTaylor's series expansion near the user's position ($\hat{x}, \hat{y}, \hat{z}$).Defining $\hat{r}$ as r_i at the position($\hat{x}, \hat{y}, \hat{z}$) we can have

$$\Delta r = r_i - \hat{r}_i \cong e_{i1}\delta_x + e_{i2}\delta_y + e_{i3}\delta_z + c \cdot t_b + v_{ri} \qquad (2)$$

Where (δ_x, δ_y, δ_z)are the coordinate offsets of (x, y, z):

$$e_{i1} = \frac{\hat{x} - X_i}{\hat{r}_i}, \quad e_{i2} = \frac{\hat{y} - Y_i}{\hat{r}_i}, \quad e_{i3} = \frac{\hat{z} - Z_i}{\hat{r}_i},$$

$$\hat{r}_i = \sqrt{(\hat{x}-X_i)^2 + (\hat{y}-Y_i)^2 + (\hat{z}-Z_i)^2} 。$$

$$(e_{i1}, e_{i2}, e_{i3}), i = 1, 2, \ldots, n. \qquad (3)$$

Eq. (3) presentsthe vector of line of sightfrom the user to the satellite. The linearized equations can be expressed as

$$z = H\delta + v \qquad (4)$$

$$z = \begin{bmatrix} r_1 - \hat{r}_1 \\ r_2 - \hat{r}_2 \\ \vdots \\ r_n - \hat{r}_n \end{bmatrix}, \quad \delta = \begin{bmatrix} \delta_x \\ \delta_y \\ \delta_z \\ c \cdot t_b \end{bmatrix},$$

$$v = \begin{bmatrix} v_{r1} \\ v_{r2} \\ \vdots \\ v_{rn} \end{bmatrix}, \quad H = \begin{bmatrix} e_{11} & e_{12} & e_{13} & 1 \\ e_{21} & e_{22} & e_{23} & 1 \\ \vdots & \vdots & \vdots & \vdots \\ e_{n1} & e_{n2} & e_{n3} & 1 \end{bmatrix}$$

Using least-square (LS) algorithm,Eq. (4) canbe solved to obtain the vector δ,

$$\delta = (H^T H)^{-1} H^T z \qquad (5)$$

Assuming that the pseudo-range errors are independent and have the same variances. Then, we can define the value of GDOP as

$$GDOP = \sqrt{tr(H^T H)^{-1}} \qquad (6)$$

It can make sure that can select the best satellite set when using inverse matrices calculate the value of GDOP, but the calculation is too complicated. In this paper, we proposed a method that used neural network with gradient descent adaptive learning rate training algorithm (GDA) to approximate the value of GDOP.

III. Neural Network

The artificial neural network (ANN) has the ability to learn, and it is an imitation of biological neural network information processing system, parallel decentralized processing based on the calculation model.Neural network mainly be formed by a large number of artificial neurons (neuron), also known as node (node) or processing unit (processing element, PE), and has the following capabilities:

1. Learning and memory ability: by adjusting the weight of the network to learn and remember the input and output between the mapping relationships to produce close to the desired output value of the output parameters.
2. Parallel computing ability: the ability can accept multiple messages at the same time, and can apply to parallel processing procedures. Each neuron has a separate processing ability; it means that will not be affected by other neurons.
3. Error tolerance: the information storage method is using decentralized memory. For a small part of the incomplete information or noise input, it also can make the right treatment.

The gradient descent adaptive learning rate training algorithm had made some changes in the learning rate.First, to calculate the output and error in each training, then using the current learning rate to calculate the new weight value and new error. If the new error exceeds the old error of 1.04 times, it will replace the old weight value and the learning rate will be 0.7 times of the original learning rate. If the new error less than the old error, it will increase the learning rate to 1.05 times of the original learning rate.

IV. Proposed Network Architectures Forgo Approximation

The method of calculating the geometric dilution of precision by using the inverse matrix is easy to cause the computational burden.The articles[8] and [9] proposed the use of traditional back-propagation neural network learning measurement matrix and eigenvalue (eigenvalue) reciprocal relationship, the three-dimensional environment to estimate the geometric dilution of precision. In this paper, the method of approximating thegeometric accuracy factor of the traditional backpropagation algorithm is extended to the approximate geometric dilution of precision by using the gradient descent adaptive learning rate training algorithm.

The following describes the six "Input / Output" mapping relationships in a two-dimensional environment. These architectures are based on a three-tier network architecture and can be expressed as "number of input layers - number of hidden layers - number of output layers". The relationship between the six mapping mechanisms, as shown in Fig. 1.

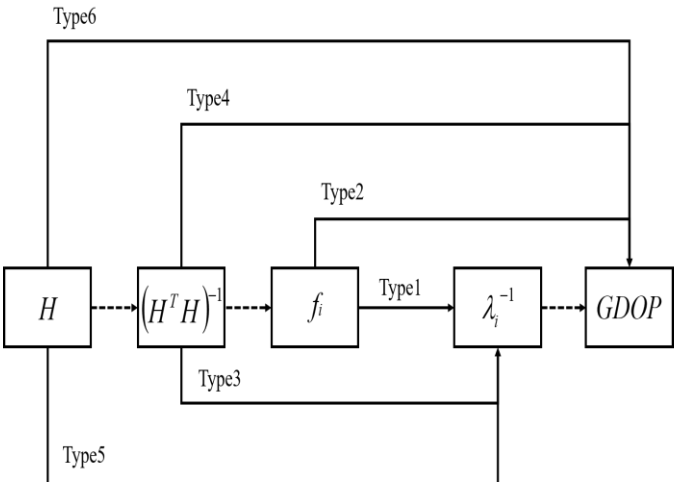

Fig. 1. "Input / Output" mapping relationships.

The articles [10] and [11] proposed the learning relationships between input and output in the traditional neural network using the measurement matrix and the eigenvalue to approximate the value of GDOP without using inverse matrix.The others relationships between the input and output was proposed for back-propagation neural network in [12]. We used the mapping relationships between the input and output, and extend to the neural network with GDA.Furthermore, we proposed two mapping relationships for the simulation to compare the performance.

● Type 1: three inputs are mapped to three outputs

$$f_1(\lambda) = \lambda_1 + \lambda_2 + \lambda_3 = trace(H^T H)$$
$$f_2(\lambda) = \lambda_1^2 + \lambda_2^2 + \lambda_3^2 = trace[(H^T H)^2]$$
$$f_3(\lambda) = \lambda_1 \cdot \lambda_2 \cdot \lambda_3 = \det(H^T H)$$

Input: $(f_1, f_2, f_3)^T$

Output: $(\lambda_1^{-1}, \lambda_2^{-1}, \lambda_3^{-1})^T$

● Type 2:three inputs are mapped to one output

Input: $(f_1, f_2, f_3)^T$

Output: $GDOP$

● Type 3:six inputs are mapped to three outputs

$$H^T H = \begin{bmatrix} B_{11} & B_{12} & B_{14} \\ & B_{22} & B_{24} \\ sym & & B_{44} \end{bmatrix}$$

Input: $(B_{11}, B_{12}, B_{14}, B_{22}, B_{24}, B_{44})^T$

Output: $(\lambda_1^{-1}, \lambda_2^{-1}, \lambda_3^{-1})^T$

● Type 4：six inputs are mapped to one output

Input: $(B_{11}, B_{12}, B_{14}, B_{22}, B_{24}, B_{44})^T$

Output: $GDOP$

● Type 5：twelve inputs are mapped to three outputs

Input:：$(e_{11}, e_{12}, e_{21}, e_{22}, e_{31}, e_{32}, e_{41}, e_{42}, 1, 1, 1, 1)^T$

Output: $(\lambda_1^{-1}, \lambda_2^{-1}, \lambda_3^{-1})^T$

● Type 6：twelve inputs are mapped to one output：

Input: $(e_{11}, e_{12}, e_{21}, e_{22}, e_{31}, e_{32}, e_{41}, e_{42}, 1, 1, 1, 1)^T$

Output: $GDOP$

The proposed BS selectioncriterion with best GDOP can be modified forapplication in cellular communication systems. Since the MS will always communicate with the service BS, we can always select the service BS from the seven BSs into the BS set, and combine the others three BSs to form the different BS set, and the number of the BS set will reduce from C(7,4)=35 to C(6,3)=20. By estimating the value of all the different BS set, we can choose the best BS set having the smallest value of the GDOP. The proposed method can be used for GDOP approximation, GPS, WSN, and wireless communication system. To further simplify the process, the proposedBS selection criterion first chooses the serve BS and selectsthree measurements from the other six BSs to form the BSs set.In this way, GDOP is computed for 20 possibleBSs sets and the one with the best and smallest value of GDOP is selected.

V. Simulation Results

Selecting the appropriate base station to estimate the position of the mobile station, can make the positioning error to a minimum.We choose the cellular wireless communication system as the simulation environment, which the size of each cell is the same, and the base station providing the service is in the middle, and the geometric distribution of the base station is shown in Fig.2.

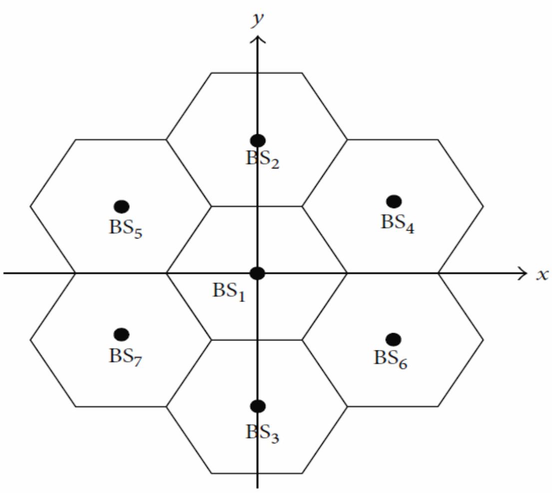

Fig. 2. Seven-cell system layout.

Each cell's radius is 5 km, the mobile station position uniform distributed in the center of the cell.We can calculate the value of GDOP for all the BSs sets, and select the minimum GDOP, using the BSs set with the minimum of GDOPto estimate the mobile station position.

The error of the wireless communication positioning system mainly effects by the influence of the non-line-of-sight propagation effect. In this paper, and the uniform distributed noise model[13] is used to simulate the two-dimensional environment.NLOS errors from all the BSs are different and assumed to beuniformly distributed over (0, U_i), for i = 1, 2, …, 7, where U_i is an upper bound. The specific variables are chosen asfollows: U_1 = 200 m, U_2 = 400 m, U_3 = 350 m, U_4 = 700 m, U_5 = 300 m, U_6 = 500 m, and U_7 = 350 m.The GDOP residual is defined as the difference between the true GDOP value and the estimated GDOP value. The GDOP residual can be used to evaluate the accuracy of the estimation.

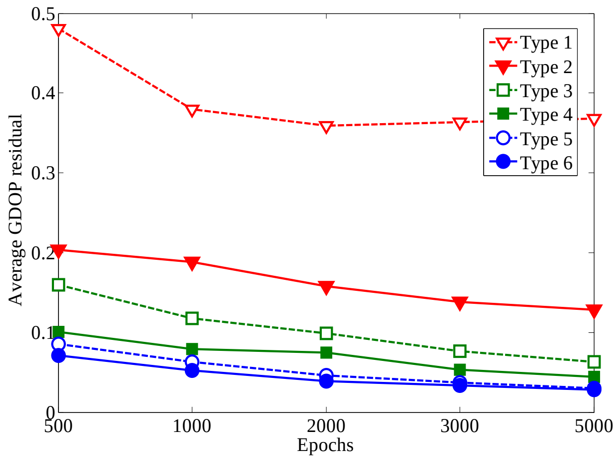

Fig. 3. Relationship between GDOP residua and Number of Training in two-dimensional environment.

Figure 3 shows the relationship between GDOP residua and number of training (Epochs) in two-dimensional environment. As the number of training increases, the average difference of the GDOP residual will also decreases.Therefore, it needs lees number of training, but can have faster convergence rate by using gradient descent adaptive learning rate training algorithm.

VI. Conclusions

In this paper, we propose a neural network architecture with gradient descent adaptive learning rate training algorithm, which approximates the GDOP in a two-dimensional environment.The simulation results show that the GDOP can be approximate by the neural network architecture with gradient descent adaptive learning rate training algorithm, and it can reduce the number of training and the computational complexity.This architecture has no limit on the number of selected measurement devices, can be applied to global positioning systems, can also be used in wireless sensor networks, and cellular communication systems. The relative position between the base station and the mobile station is an important factor affecting the positioning accuracy.If you choose any of the four base stations, will result in poor positioning accuracy.In this paper, the approximate GDOP by neural network architecture with gradient descent adaptive learning rate training algorithmcan improve the localization efficiency and reduce the influence of geometric distribution.

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