A Hybrid Location Algorithm Based on BP Neural Networks for Mobile Position Estimation

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Summary

In this paper, we propose an efficient hybrid location algorithm with BP neural networks. We choose two-layer backpropagation network for data fusions and position estimation to improve hybrid location accuracy and efficiency with TOA/TDOA/AOA parameters in mobile communication networks. So the position estimation can be optimized by network parallel processing robustly, and the inaccuracy or fuzzy problem produced by conventional location algorithm can be overcome effectively. In the paper, the model of the data fusion with multi-parameters of TOA/TDOA/AOA is set up to optimize network hybrid location configuration, The Simulation results show that the algorithm with BP neural networks can work effectively.

Introduction

The data fusion based on neural network (NN) has been applied in many fields extensively. Cho. Sung-bae proposed a neural network model integrated with the fuzzy logic and genetic algorithm in reference [1]. And some scholars presented several opinions on the wireless location application with neural network, such as, Sandrine Merigeault etc. proposed a data fusion model based on genetic algorithm for mobile location [2]; Zamiri-Jafarian, H. etc. proposed a multi-layer perceptron neural networks with hierarchical structure to realize TOA/AOA hybrid location [3]; Muhammad etc put forwards a multi-layered perceptron NN model to predict mobile users' positions for the position estimation and prediction with hybrid location[4].

Based on the above researches, a hybrid location algorithm with BP neural network for mobile position estimation is proposed to solve some problems such as location parameter fuzzy and greater change in location error caused by widely-distributed computation.

BP networks are multi-layer backpropagation networks, by which input vectors and the corresponding target vectors are used to train a network until it can approximate a function, and tend to give reasonable answers when presented with inputs that they have never seen. This makes BP networks useful in location signal processing and prediction where hybrid location plays a dominant role.

In this paper, we simulate the BP neural network with three kind of location parameters of TOA/TDOA/AOA to realize the hybrid location computation, where different location parameters came from different base channels are set in the input layer, and the coordinate parameters as position estimation is presented in the output layer. So the problems of multi parameter processing with the integrated location algorithm based on fuzzy identification and data fusion [5] can be easily carried out. The simulation results show that more precise and reliable location processing can be achieved by the hybrid location algorithm with BP neural network than the conventional hybrid location algorithm.

2. The structure model for hybrid location based on BP NN

Until now, the most neural networks algorithms applied in the mobile location researches are build in hierarchical structure model with BP networks, because it is relatively simple in structure and easy for computation, but it converges relatively slowly, and needs more neurons to get needed output accuracy[6]. The Elman recurrent networks are also adopted to apply in the location processing and position prediction [7], but it is more complex and needs more computation for its feedback connection from the output of the hidden layer to its input. In this paper, two layers structure of BP neural network is used, in which vector input of multi parameter, the hidden layer, the output layer and the position estimation output are included. The BP network structure for hybrid location algorithm is shown in figure 1.

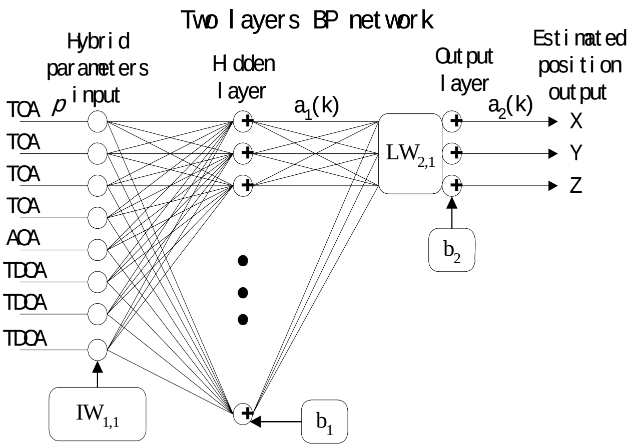

Fig. 1. The BP network structure as hybrid location algorithm

The computation formulas are as below:

$$a_1(k) = \tan sig(IW_{1,1}p + b_1) \quad (1)$$

$$a_2(k) = purelin(LW_{2,1}a_1(k) + b_2) \quad (2)$$

In which IW1,1 is the input weight，LW2,1 is the weight of the second layer,b1 and b2 is the bias.

The input: because at least four TOAs or three TDOAs are needed for conventional location algorithm to get position solution, and also only an AOA parameter combined with a TOA or TDOA are needed for hybrid location algorithm, so in this hybrid location algorithm with BP network, we choose a group of channel data as input vector, which include four TOAs, three TDOAs and an AOA parameter measured over four channels.

The hidden layer: the hidden layer's or a tansig layer's neuron as processing unit is usually a nonlinear function, which transforms the input parameter into other form of parameter as output. For hybrid location with BP network, that is to transform

$$[X\ Y\ Z] = f\ (TOA/TDOA/AOA) \quad (3)$$

as

$$[X\ Y\ Z] = W{*}a(TOA/TDOA/AOA) \quad (4)$$

In other words, for sufficient high order terms, there always exist weight values W such that the BP structure W*a(x), can approximate f (TOA/TDOA/AOA) to any degree of accuracy, in a compact domain. By increasing the neurons' number in the hidden layer, the location accuracy can be improved, but more computation amounts are needed at same time.

Because less number of the inputs is used in this paper, and the structure model for hybrid location algorithm is mainly considered in this paper, 60 neurons are chosen as the neural number of tansig layer. the tangent function of tan-sigmoid is adopted, so f(x)=tansig(x), as to its input values can be arbitrary but output values are limited between -1 and +1.

The output layer: The output layer is a purelin layer composed of three neurons with the linear transfer function purelin. That is f(x) = kx.

The output: giving out estimated positions (x,y,z) of mobile terminal.

The weight values for connecting and learning in neural network can be optimized by application combined genetic algorithm with artificial neural network. The optimum weight values including connecting weight values, network structure and learning rules' evolution can be obtained with GA's searching ability [8].

The genetic algorithm exhibits its characteristic of global search and quick convergence ability for successful application of hybrid location and management in references [9][10][11]. Combining the genetic algorithm with neural network can be well applied in mobile hybrid locations [6]. So that not only bring into play the wide mapping ability of neural network, but also overcome the disadvantages of NN such as converged slowly and easily trapped into the local minimal point.

The hybrid location algorithm combined genetic algorithm with neural network can be successfully used for the position estimation by time series analyzing. In the algorithm it is usually hard to make quantities estimation for the fuzzy training signals and data with noise. However, if we can make use of the genetic algorithm to learn, these problems can be overcome and the NN's performance can be improved greatly. The configuration of weight value optimizing is shown in figure 2.

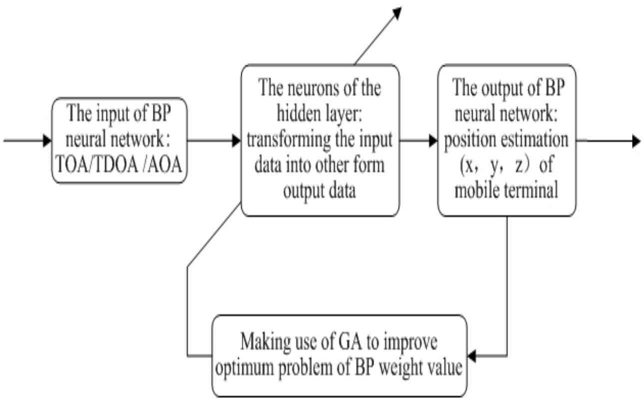

Fig. 2. The configuration of weight value optimizing

By minimizing the fitness function,

$$\begin{cases} \min\limits_{X} & f(\mathbf{X}) = \min\left(\mathrm{f}\ (\mathrm{TOA/TDOA/AOA}) - \mathrm{a}\ (\mathrm{W})\right) \\ & s.t. \quad \mathbf{X} \in \mathbf{R} \\ & \mathbf{P} \subseteq \mathbf{U} \end{cases} \tag{5}$$

The optimum weight values for hybrid location algorithm can be achieved at the present time. In the formula above: $\mathbf{X} = [x_1, x_2, \ldots, x_n]^T$ is the decision variable, f(x) is the goal function, U is the fundamental space, R is a subset of U.

Obviously it may lead to the simultaneous satisfaction of the separable conditions, thus yielding highly separable classes in the feature space. Prior to calculating (5), the border of each class should be determined. Efficient polygonal approximation algorithms can be used for this purpose.

The genetic algorithm can be applied to trace the weights or structure of neuron connection and make a dynamic adjustment to the optimum weight values. The whole algorithm process is showed as figure 3.

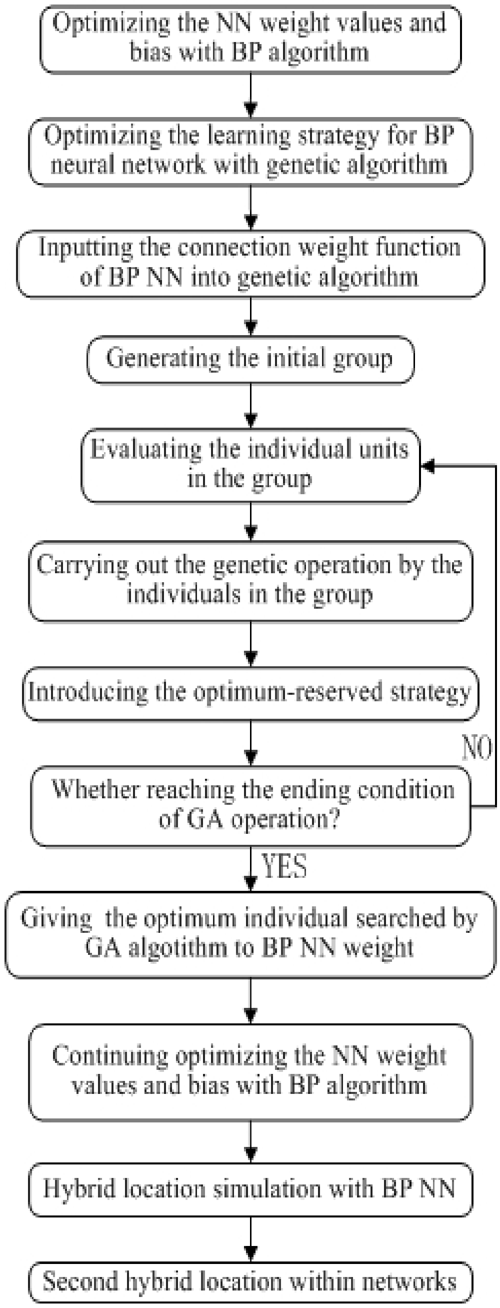

Fig. 3. Logic diagram for hybrid location algorithm with BP networks

The whole hybrid location model with NN and fuzzy data fusion in mobile network is shown as figure 4.

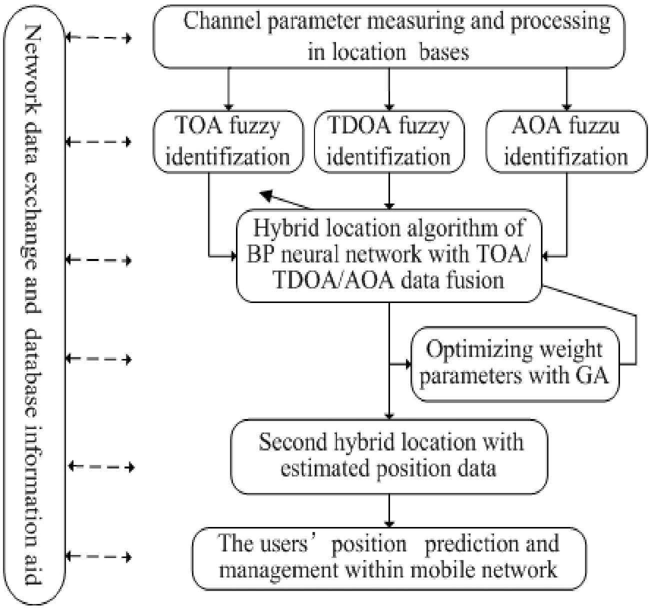

Fig. 4. The hybrid location model with NN & data fusion

3. The simulation and result analysis of hybrid location algorithm

The condition of simulating process is listed as following:

The positions for four known bases are: G_{11}(-1500, -600, 400), G_{21}(1400, -500, 150), G_{31}(100, 900, 130) and G_{41}(-400, 1400, 300).

The mobile position point is starting at G_i (-60, 80, 20), by which and four known positions, the all TOA/TDOA/AOA data of channel parameters for hybrid location can be created. For the reason of visibility and compare, we choose 50 location points to get an equidistant linear locus.

The measurement error of transmitting time for training signal is a randomly-distributed error adding up error of COST259 model.

Assume that all measured parameters within mobile network are synchronous.

The trainbfg algorithm is used to make a 500-step training to learn.

The simulation data in BP network is same as training dada produced by location point and bases with random error and COST259 model error, but also plus 0.03% random error in simulation data to check behavior in the presence of a model mismatch between the prediction model and the process model in hybrid location algorithm.

The simulation results of hybrid location with BP NN for two time are shown in figure 5, in hidden layer there are respectively 60 neurons and 160 neurons to learn training and simulate hybrid location. In the figure 5, * represents the actual users' position, and o represents the users' position from simulating with 60 neurons, and + represents the users' position from simulating with 160 neurons.

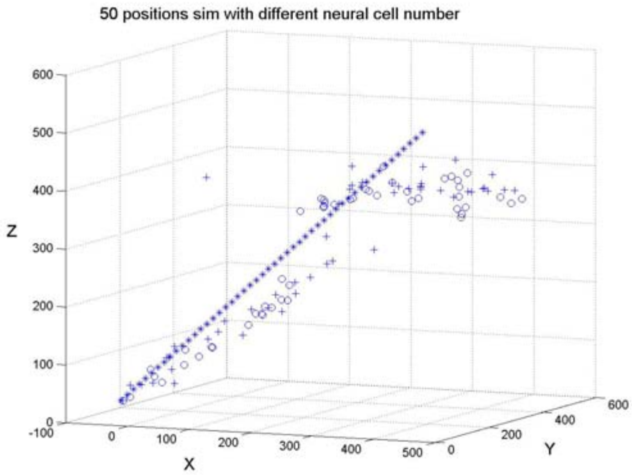

Fig. 5. Simulation results of hybrid location with 60 and 160 BP neurons

By figure 5 we can see that the less neuron, the larger the simulation location error. Adding more neuron number with the same parameters and structure, the location accuracy can be improved obviously.

With the results in figure 5, the position error compare of hybrid location algorithm is drawn in figure 6, where o is the position error simulating with 60 neurons, * is the position error simulating with 160 neurons.

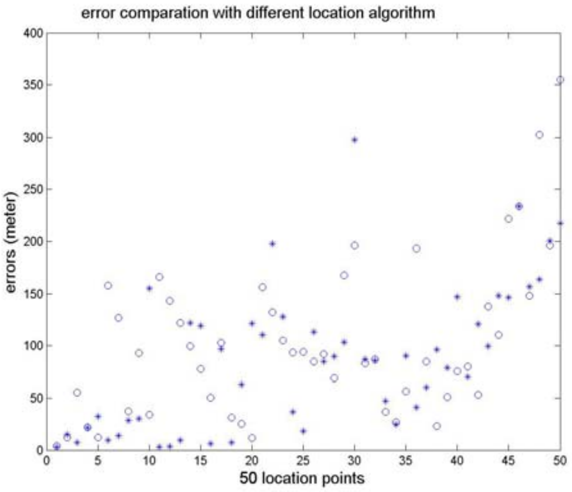

Fig. 6. Error compare of hybrid location with different neurons

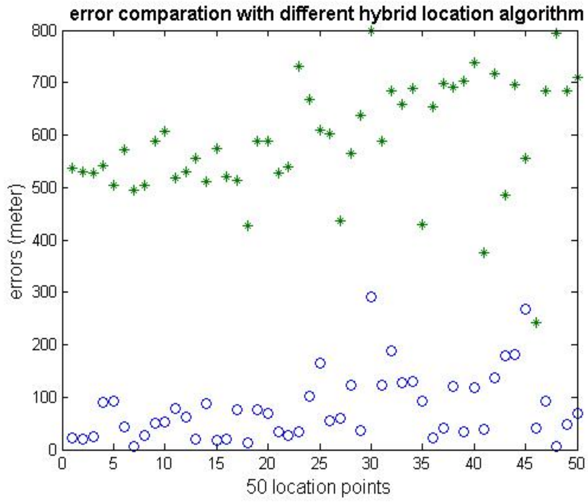

Fig. 7. Error compare with two kinds of hybrid location algorithm

From simulation we can see that while the conventional hybrid location algorithm leads to more location error in the interference environment with the same error, the BP neural network has better simulation location accuracy. In figure 7, the comparing picture of position bias results are showed which adopts NN hybrid location algorithm with the one with the conventional hybrid location algorithm. While * is the users' position error from the conventional hybrid location simulation, o is the users' position error from simulating 260 neurons, which can reach the location accuracy given by FCC ,but requiring more neurons to reach the hybrid location accuracy and training convergence rate.

4. Conclusions

We have presented a hybrid location algorithm with BP NN for mobile location system, aiming at precise and robust hybrid location. The advantages of the approach are that: Multi parameters of TOA/TDOA/AOA data for hybrid location processing can be directly inputted into BP NN to get optimum position estimation. By introducing GA feedback interlink the decision variables and weights in BP NN can be adjusted to optimum programming. The simulation results show that more precise and reliable position estimation can be achieved by the hybrid location algorithm with BP NN than conventional estimation.

References

1. Cho, Sung-Bae, Fusion of neural networks with fuzzy logic and genetic algorithm, Integrated Computer-Aided Engineering, v 9, n 4, 2002, p 363-372.

2. Merigeault, S.; Batariere, M.; Patillon, J.N., Data fusion based on neural network for the mobile subscriber location, Vehicular Technology Conference Fall 2000. IEEE VTS Fall VTC2000. 52nd Vehicular Technology Conference: (vol.2) 536-541.

3. Zamiri- Jafarian, H.; Mirsalehi, M.M.; Ahadi- Akhlaghi, I.; Keshavarz, H., A neural network-based mobile positioning with hierarchical structure, 57th IEEE Semiannual Vehicular Technology Conference. VTC 2003 : (vol.3) 2003-7.

4. Muhammad J, Hussain A, Neskovic A, Magill E, New neural network based mobile location estimation in a metropolitan area, ARTIFICIAL NEURAL NETWORKS: FORMAL MODELS AND THEIR APPLICATIONS- ICANN 2005, PT 2, PROCEEDINGS LECTURE NOTES IN COMPUTER SCIENCE 3697: 935-941 2005.

5. Zhao Ping, Shi Haoshan, The Integrated Location Algorithm Based on Fuzzy Identification and Data Fusion with Signal Decomposition, Second International Conference Proceedings On Natural Computation and Fuzzy Systems and Knowledge Discovery, ICNC'05-FSKD'05, LNAI 3613, p383-387.

6. Salcic, Zoran; Chan, Edwin, Mobile station positioning using GSM cellular phone and artificial neural networks, Wireless Personal Communications, v 14, n 3, Sep, 2000, p 235-254.

7. X. Z. Gao, S. J. Ovaska and A. V. Vasilakos, A modified Elman neural network-based power controller in mobile communications systems, Soft Computing - A Fusion of Foundations, Methodologies and Applications, Volume 9, Number 2, February 2005: 88 – 93

8. G. A. Rovithakis, M. Maniadakis, and M. Zervakis, A Hybrid Neural Network/Genetic Algorithm Approach to Optimizing Feature Extraction for Signal Classification, IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS—PART B: CYBERNETICS, VOL. 34, NO. 1, FEBRUARY 2004:694-702.

9. Karaoglu, Bahar; Topcuoglu, Haluk; Gurgen, Fikret, Evolutionary algorithms for location area management, Lecture Notes in Computer Science, v 3449, Applications on Evolutionary Computing-EvoWorkshops 2005: EvoBIO, EvoCOMNET, EvoHOT, EvoIASP, EvoMUSART, and EvoSTOC, Proceedings, 2005, p 175-184.

10. Krzanowski, R.M.; Raper, J., Hybrid genetic algorithm for transmitter location in wireless networks, Computers, Environment and Urban Systems, v 23, n 5, Sep, 1999, p 359-382.