

A Parameters Optimization of Synergetic Neural Network Based on Differential Evolution Algorithm

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Abstract

Synergetic neural network (SNN) is a top-down network to explain the phase transition and self-organization in non-equilibrium system. The network parameters have a crucial impact on the recognition performance of synergetic neural network. At present, there is no good way to control and adjust the network parameters. To solve these problems, an improved parameters optimization algorithm based on differential evolution algorithm is proposed and implemented in this paper. There are two main works in this paper. Firstly, a semantic analysis model based on synergetic neural network is presented. Secondly, differential evolution algorithm is used to search the global optimum of network parameters in the corresponding parameter space. The experiments showed that the optimization algorithm can improve the synergetic recognition performance.

Keywords: SNN , DE , optimization algorithm .

1. Introduction

Synergetic theory is the science proposed by Haken [1,2] to describe high dimension and nonlinear problem as a set of low-dimension nonlinear equations. Haken proposed to put synergetic theory into a new field: synergetic neural network. At present, the mainstream studies of SNN focus on the selection of prototype pattern vector [3], setting of attention parameter [4, 5] and reconstruction algorithm of order parameters [6] and so on. The network parameters are very important for better recognition performance. The change of attention parameters will lead to completely different recognition results. There is no effective way to control parameters.

Differential evolution algorithm (DE) [6] is a class of swarm intelligence optimization algorithm based on the behavior of animals by Rainer Storn and Kenneth Price. Differential evolution algorithm is very suitable for solving a variety of numerical optimization problem, making the algorithm quickly became a hot topic in the current optimization field.

DE has been applied successfully to all kinds of optimization problems such as constrained optimization problems [7], chaotic systems[8], engineering design [9-11], toroidal pressure vessels[12], flow shop scheduling[13], milling operations[14], islanded micro-grid[15] and other areas [16-20]

There are two main contributions in this paper. Firstly, we introduce SNN model to semantic parsing which can better handle fuzzy matching of semantic information. Secondly, we propose an improved SNN model based on differential evolution algorithm which can effectively choose network parameters.

This paper is organized as follows. Firstly, the basic theory of synergetic neural network and differential evolution algorithm is presented. Secondly, a Semantic role labeling model based on SNN and parameters optimization algorithm based on differential evolution algorithm are introduced. Finally some experimental tests, results and conclusions of the optimization algorithm are given on the systems.

2. A Brief Introduction to DE and SNN

2.1 Background of SNN

A dynamic equation can be given for an unrecognized pattern q :

$$\dot{q} = \sum_{k=1}^M \lambda_k v_k (v_k^+ q) - B \sum_{k \neq k'} (v_k^+ q)^2 (v_k^+ q) v_k - C(q^+ q)q + F(t).$$

Where q is the status vector of input pattern with initial value q_0 , λ_k is attention parameter, v_k is prototype pattern vector, v_k^+ is the adjoint vector of v_k that satisfies

$$(v_k^+, v_{k'}^T) = v_k^+ \cdot v_{k'}^T = \delta_{kk'}.$$

$$\text{Where } \delta_{kk'} = \begin{cases} 1 & k = k' \\ 0 & k \neq k' \end{cases}$$

Potential function is:

$$V = -\frac{1}{2} \sum_{k=1}^M \lambda_k (v_k^+ q)^2 + \frac{1}{4} B \sum_{k \neq k'} (v_k^+ q)^2 + \frac{1}{4} C \left(\sum_{k=1}^M (v_k^+ q)^2 \right)^2$$

Kinetic equation:

$$\dot{q} = -\frac{\partial V}{\partial q^+} \quad \text{和} \quad \dot{q}^+ = -\frac{\partial V}{\partial q}$$

Corresponding dynamic equation of order parameters is

$$\dot{\xi}_k = \lambda_k \xi_k - B \sum_{k \neq k'} \xi_{k'}^2 \xi_k - C \left(\sum_{k=1}^M \xi_{k'}^2 \right) \xi_k.$$

2.2 Background of DE

Suppose the individual i of generation G is represented as $X_{iG} = (x_{iG}^1, x_{iG}^2, \dots, x_{iG}^D)$, $i = 1, 2, \dots$. Basic operations such as mutation, selection and crossover is the basis of the difference algorithm.

(1) mutation operation

A individual can be generated by the following formula:

$$X_{i,G+1} = X_{r1,G+1} + F * (X_{r2,G} - X_{r3,G}),$$

Here $r1, r2, r3$ are random numbers generated, Variation factor F is a real number.

(2) Crossover operation

In difference algorithm, the cross operate is introduced to the diversity of the new population. New individuals can be represented as follow:

$$X_{i,G+1} = (x_{1i,G+1}, x_{2i,G+1}, \dots, x_{Di,G+1}), i = 1, 2, \dots$$

Where

$$x_{ji,G+1} = \begin{cases} V_{ji,G+1}, & \text{if } (randb(j) \leq CR) \text{ or } (j = mbr(i)) \\ V_{ji,G+1}, & \text{if } (randb(j) > CR) \text{ and } (j \neq mbr(i)) \end{cases} \quad (j = 1, 2, \dots, D),$$

$randb(j)$ is uniformly distributed in the interval [0, 1], CR is crossover probability. $mbr(i)$ means a random number.

(3) Selection operation

Selection operation is a greedy strategy, the candidate individual generated from mutation and crossover operation competition with target individual.

$$x_{i,G+1} = \begin{cases} U_{i,G}, & \text{if } (f(U_{i,G}) > f(x_{i,G+1})) \\ x_{i,G+1}, & \text{if } (f(U_{i,G}) \leq f(x_{i,G+1})) \end{cases}, \text{ Where } f \text{ is the fitness function.}$$

The basic differential evolution (DE) algorithm is shown as Algorithm 1.

- 1) Initialize the number of population NP , the maximum number of evolution $Max\ int\ er$, the scale factor and cross-factor;
- 2) Initialize the population pop ;
- 3) Follow the $DE / rand / 1 / bin$ policy enforcement options, and produce a new generation of individual:
 - a) Mutation operation;
 - b) Crossover operation;
 - c) Selection operation.
- 4) Until the termination criterion is met.

Algorithm 1. The differential evolution algorithm

3. Semantic role labeling based on SNN

Semantic role labeling(SRL) [21-22] is an important problem in natural language processing to determine the relation between the predicate in a sentence and its corresponding argument.

3.1 Feature Selection

At present, state-of-the-art SRL system is based on dependency syntactic tree. The performance of current semantic role labeling systems heavily depends on the performance of features. It is necessary to introduce more abundant features. We use some types of features.. The features used in our system are listed in Table 1.

Table 1. The Features with Word Sense Used in our System

ID	Feature name	Description
1	predicate lemma	The word lemma of predicate
2	predicate POS	Part of speech of predicate
3	predicate voice	The active voice and passive voice of predicate
4	path	The dependency chain from the current node to the

		current predicate via nodes of
5	Dependency	The dependence of corresponding nodes
6	headword	The word lemma of the current node's father node
7	The dependency chain of predicate child	The dependency chain of all the children nodes
8	The POS chain of predicate brother	The POS chains of all the current predicate brothers
9	The dependency chain of predicate brother	The dependency chains of all the current predicate brothers
10	predicate	The predicate itself
11	The POS chain of predicate children	The POS chains of all the current predicate children
12	Dependency word	The current node .

3.2 Semantic Role Labeling Model

A method for label semantic roles using Synergetic Neural Network technique is presented in Figure1.

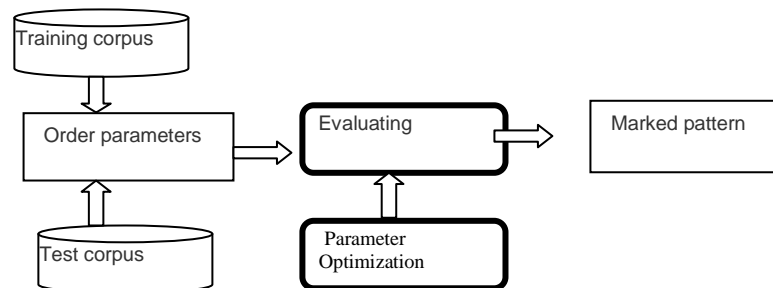


Figure 1. A Method for Label Semantic Roles using Synergetic Neural Network

The Semantic role labeling based on SNN can be described as follow:

- 1) construct pattern $p_l (l = 1, 2 \dots)$ and possible roles $R_k (k = 1, 2 \dots)$.
- 2) Combination of all possible roles of $p_l (l = 1, 2 \dots)$, obtain all the possible roles chains $R_k (R_{k1}, R_{k2}, \dots, R_{kn}) (k = 1, 2 \dots, m)$.
- 3) Set $\lambda_k = \gamma \times f(R_{k1}, R_{k2}, \dots, R_{kn}), (k = 1, 2 \dots, m)$.
- 4) DE algorithm are used to search the global optimum parameters in the corresponding parameter space.
- 5) Get best roles chain.

Algorithm 2 Semantic role labeling based on SNN

4. A parameters Optimization Algorithm based on Differential Evolution Algorithm

The potential function of SNN is:

$$\dot{\xi}_k = \lambda_k \xi_k - B \sum_{k' \neq k} \xi_{k'}^2 \xi_k - C \left(\sum_{k'=1}^M \xi_{k'}^2 \right) \xi_k \dots \dots (1)$$

The network parameters λ_k directly influence on the recognition performance. Each change will lead to the change of the sizes of the attracting fields of all stable fixed points.

The optimization of network parameters based on DE can be described as follow.

- 1) Obtain feature vectors from train corpus and test corpus, construct prototype pattern v_k ($k = 1, 2, \dots$) and test pattern q_l ($l = 1, 2, \dots$).
- 2) Calculate initial order parameter ξ_{lk} according to equation (11).
- 3) DE optimization algorithms are used to search the global optimum parameters (γ, B, C) of SNN in the corresponding parameter space.
- 4) Get best mangrove categories through the evaluating of order parameter equation (10).

Algorithm 2. The optimization of network parameters based on DE algorithm.

5. Experiment

In our experiments, SNN is trained to identify and classify the predicates semantic roles, the SRL system will address not only propositions around verbal predicates but also around nouns. We used precision, recall and F1 values as evaluation indicators.

$$F1 = \frac{2 \times precision \times recall}{precision + recall}$$

For comparison, we use three optimization strategies:

SNN model with fixed parameters (SNN)

SNN model with parameter optimization based on DE (SNN+DE)

In strategies ①, we set $\lambda_k = 1.2$, $B=C=1$. In strategies ②, DE algorithms are used to search the global optimum parameters (γ, B, C) of SNN in the corresponding parameter space.

The parameter setting of DE is shown as table 2.

Table 2. The Parameter Setting of DE

Algorithm	Population size	pm	pc	Maximum number of iterations
DE	30	0.6	0.5	10

Table 3. The Performance of Different Systems on Test Set

Algorithm	Precision	Recall	F1-score
SNN	84.64	83.43	84.03
SNN+DE	84.93	84.62	84.77

The performance of these systems on test set is shown in Table 3. From Table 3, we can see the improved algorithm can improve the precision, recall, and F1 compared with baseline system. So optimization algorithm is essential for better performance. But at the same time, a significant gap still exists between the results and the gold standards of manually compiled semantic parsing. In future work, we will propose more effective algorithm to improve the performance.

6. Conclusions

In the paper, we construct a semantic analysis base on improved SNN model. Experiments show the parameters optimization algorithm has a higher performance for semantic analysis. In the future, we will focus on the following two aspects :

- 1) The interaction between roles has important influence on the performance of semantic analysis, we will find out more constraints.
- 2) The parameters of DE algorithm have a critical influence for better performance. We will introduce adaptive parameter setting method.

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