가변학습율과 온라인모드를 이용한 개선된 EBP 알고리즘

이태승[0] 최호진
한국항공대학교, 한국정보통신대학교
thestaff@hitel.net[O], hjchoi@icu.ac.kr

Improved Error Backpropagation by Elastic Learning Rate and Online Update

Tae-Seung Lee[0] Ho-Jin Choi
Hankuk Aviation University, Information and Communications University

Abstract

The error-backpropagation (EBP) algorithm for training multilayer perceptrons (MLPs) is known to have good features of robustness and economical efficiency. However, the algorithm has difficulty in selecting an optimal constant learning rate and thus results in non-optimal learning speed and inflexible operation for working data. This paper introduces an elastic learning rate that guarantees convergence of learning and its local realization by online update of MLP parameters into the original EBP algorithm in order to complement the non-optimality. The results of experiments on a speaker verification system with Korean speech database are presented and discussed to demonstrate the performance improvement of the proposed method in terms of learning speed and flexibility for working data of the original EBP algorithm.

1. Introduction

The error-backpropagation (EBP) algorithm is prevailing in multilayer-perceptron (MLP) learning. For training MLPs, the EBP algorithm is widely used due to its robustness in overfitting and its economical efficiency in terms of the number of learning parameters and the size of required memory [1], [2]. In the EBP algorithm, selection of an appropriate constant learning rate is important for the learning speed and recognition rate of an MLP. In general, an "optimal" learning rate lies within a range of "effective" learning rates which provide near-best performance [3]. This range is obtained from testing data and then applied to operating data, assuming that the properties of the testing data are the same as those of the operating data.

We notice that the original EBP algorithm has a drawback in selecting an optimal learning rate because it uses learning rates which are constant. In reality, the optimal learning rate does change according to the global and local progress of a given learning experiment. The learning rate in the initial stage of learning may be different from that of the final stage. Learning rates for various learning models may not be the same even in the same stage of learning. Moreover, for the range of effective learning rates, the properties of operating data are likely to be different from those of testing data, contrary to the assumption mentioned above. In this case, the optimal learning rate selected for the testing data may be different from that for the operating data. Thus, it would be more reliable to keep the effective range as broad as possible. The original EBP algorithm keeps its learning rate constant for the whole process of learning, neglecting that proper learning rate may change with the progress of learning. This behavior of EBP results in lazy learning. Moreover, sticking to a constant learning rate tends to narrow down the effective range where the optimal learning rate can be located. This defect would reduce the flexibility of the EBP algorithm when applied to the operating data.

In this paper, we propose a modified EBP algorithm which adopts "elastic" learning rates within a broad effective range in the online update mode. The algorithm senses all the aspects of dynamicity in MLP learning and applies appropriate learning rates according to the progress of learning. The dynamic range of elastic learning rates is searched beforehand by applying a constant learning rate of the original EBP, in order to assure the convergence of the given learning. The elastic learning rate catches the detailed progress of learning, and the online update of the MLP parameters realizes the learning pattern by pattern. This paper discusses the performance of the proposed method through experiments using a speaker verification system based on MLPs and a Korean speech database for connected four-digit speech.

2. MLP Learning with EBP and Its Non-optimality

MLPs learn models of learning by establishing decision boundaries that discriminate the model areas. If patterns of models are fully presented in an iterative manner and internal parameters of an MLP are adjusted so that all patterns of each model are classified into their corresponding model, the decision boundaries will finally be settled within the optimal positions.

The commonly used EBP algorithm updates the weights of an MLP using the information related to a given pattern and current weights status as the following formulae:

$$\begin{aligned} w_{ij}(n+1) &= w_{ij}(n) + \Delta w_{ij}(n) \\ &= w_{ij}(n) - \eta \frac{\partial e_p(n)}{\partial w_{ij}(n)} \end{aligned} \tag{1}$$

$$e_p(n) = \frac{1}{2}\sum_{k=1}^{M} e_k^2(n) \tag{2}$$

$$e_k(n) = d_k(n) - y_k(n) \tag{3}$$

here, w_{ij} stands for weighted link from computational node j to node i, n for update count of weighted link, e_p for summation of error energies from all output nodes for given pattern p, and e_k, d_k and y_k stand for error, learning objective output, and network output, respectively, of output node k. M designates the number of output nodes and η the learning rate determining how much portion of the change of weighted link Δw_{ij} is applied to the update.

The objective of learning is in general designated to 1 if the output node corresponds to the model of the current pattern, or to 0 or -1 otherwise, according to whether the type of activation function is binary or bipolar, respectively. Updates of weighted links continue until some criteria are satisfied. For a typical case, the summation of e_p's for all learning patterns goes down below a certain value. After learning is complete, the network outputs (each converging to its own objective) are derived from the learned weighted links and the decision boundaries are formed along the valleys between the peaks of all model areas.

To obtain the best discrimination of MLP and learning duration of the all models with the EBP algorithm, distinct learning rates η's must be searched. Too large or too small η tends to lead poor discrimination and long duration. In general, various η's need to be tested by decreasing from large to small values (or vice versa) within a suitable range, and the optimal η need to be selected to obtain the best discrimination and shortest duration of learning.

However, the optimal η for the best learning changes according to global and local progress of learning. One epoch is the duration in which all patterns to be learned are presented once. As learning epochs proceed, the temporal value of η should decrease by large to prevent the learning from oscillating around the desired objective. Even within a single epoch, proper η may differ from pattern to pattern because individual learning of a pattern progresses differently from those of other patterns. The original EBP algorithm adopts a constant η and does not consider such variation of learning progress, hence cannot achieve the optimal learning. That is, it cannot obtain both the best discrimination and the shortest duration at once.

The optimal η is located within a range of effective η's, which provide near-best performance. This range is obtained from training data and applied to working data, assuming that the properties of training data are the same as those of working data. In reality, however, the properties of working data are not necessarily the same as those of training data, simply because the amount of the latter is generally larger than that of the former and thus the latter has more variation. Accordingly, the optimal η selected for training data may not guarantee the best performance for working data. To obtain as high performance for working data as possible, it is therefore important for the range of effective η's to be as broad as possible so that more variation of working data is prepared for.

3. Proposed Method

To enable the EBP algorithm to prepare for the variation of learning progress and the difference between training and working data of an MLP, we present a modified EBP algorithm. The modification aims to achieve three goals: (1) to guarantee the convergence of learning, (2) to catch the progress of individual pattern, and (3) to realize the individual progress of each pattern to MLP.

First, to guarantee the convergence of learning. To achieve this goal we adopt a kind of "elastic" learning rate. By this means, dynamic excitation by learning patterns should not cause a given learning to become distant from the desired objective. To acquire the final convergence in learning, empirical information can be utilized that has been obtained by previous searches for training data. In the proposed method, we adopt the upper and lower limits of the constant learning rates each of which has led to convergence in a preceding evaluation using the original EBP algorithm. Any of elastic learning rates within this range will guarantee convergence.

Second, to catch the individual progress of each learning pattern. Establishing decision boundary can be analyzed by local error gradient of model-specific output node. When the local error gradient of output node k is designated as δ_k, the corresponding model generates δ_k during learning and it repulses the decision boundary which is shaped arbitrarily at the first stage of learning, establishing it gradually as borders of model areas. δ_k is calculated by error e_k and the first differential function of output activation function φ. The value of the first differential function is obtained from the weighted and summed input v_k to output node k. The calculus form of δ_k is expressed as follows:

$$\delta_k = e_k \cdot \varphi'(v_k) \tag{4}$$

e_k and $\varphi'(v_k)$ yield significant values to the patterns located nearby decision boundary and the patterns in the areas of other models except the output node k over decision boundary. Learning continues until δ_k is minimized for the given pattern and the value of δ_k shows how much the pattern must be learned hereafter at a point of learning time. Among the ingredients of δ_k, e_k can more effectively present the progress of learning of a pattern due to its linearity as seen in Eqn 3, so it is adopted to catch the individual progress of each learning pattern.

Third, to apply the individual progress of the given pattern to an MLP. The offline update mode of the EBP algorithm calculates the changes of weighted link vector for all learning patterns, averages them, and updates the weighted link vector once per an epoch as follows:

$$w_{ij}(t+1) = w_{ij}(t) - \frac{\eta}{N}\sum_{p=1}^{N}\frac{\partial e_p(t)}{\partial w_{ij}(t)} \tag{5}$$

where, t stands for epoch count and N for the number of patterns given during an epoch. Compared with the offline mode, the online mode shown as Eqn. 1 updates the weighted link vector whenever the change of weighted link vector is calculated for each pattern. In the offline mode, all the patterns have to be learned with the same learning rate. In the online mode, however, each pattern can have opportunity to be learned with the proper learning rate as to its local learning progress because of its property of pattern by pattern update.

The three means presented above construct the following formulae for the update of weighted link vector in the proposed method:

$$f(n) = \frac{e_C^{\,2}(n) - e_{OBJ}}{R_{ACT} - e_{OBJ}} \tag{6}$$

$$\eta(n) = \begin{cases} f(n)\cdot L_{HIGH} & \text{if } f(n)\cdot L_{HIGH} > L_{LOW} \\ L_{LOW} & \text{otherwise} \end{cases} \tag{7}$$

$$w_{ij}(n+1) = w_{ij}(n) - \eta(n)\frac{\partial e_p(n)}{\partial w_{ij}(n)} \tag{8}$$

where, $e_C^{\,2}(n)$ stands for error energy form of the error yielded by the output node to where the given pattern belongs, R_{ACT} for the possible range of the error energy for the same output node, e_{OBJ} for the objective error energy of given learning, and L_{HIGH} and L_{LOW} for the upper and lower limit, respectively, such that the range established by them guarantees the learning to converge. $f(n)$ stands for error energy normalization function to gauge the learning progress of the pattern and normalize it into the range from 0 to 1. $f(n)$ presents high values for deficiently learned patterns and low values for sufficiently learned patterns. $\eta(n)$ stands for elastic learning rate scaled from the normalized error energy of the pattern into the range limited by L_{HIGH} and L_{LOW}. Eqn. 8 is the finally obtained expression which the elastic learning rate is adopted into the original EBP algorithm in the online mode.

4. Performance Evaluation

The experiment aims to demonstrate the performance of the proposed method as compared to the original EBP algorithm, using a speaker verification system and conditions of experiment appeared in [4]. Here we first obtain the best performance of the system using the original online EBP algorithm and the optimized performance using the proposed method. Then, the two methods are compared for learning duration and operational flexibility to conclude that the proposed method exhibits superior performance.

In the results of our experiment, error rate stands for equal error rate, and the number of learning epochs for average number of epochs used to enroll a speaker for an isolated word. These values are calculated by taking the average of values obtained from three trials of learning, each trial being set to the same MLP conditions.

Fig. 1 depicts the changes in the performance of the system implemented using the original online EBP algorithm, measured with respect to various values of learning rate and objective error energy. The values in the figure chase the trajectories of the numbers of learning epochs and verification errors, with a fixed value of 0.01 for learning objective error energy in the case of figure (a) and a fixed value of 0.5 for learning rate in the case of figure (b). In figure (a), the best learning rate, 0.5, is obtained when the number of learning epochs is 172.3 and the error rate is 1.65 %. In figure (b), the best learning objective error energy, 0.005, is obtained when the number of learning epochs is 301.5 and the error rate is 1.59 %.

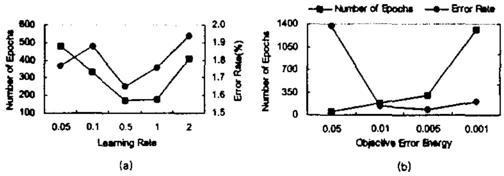

Fig. 1. Performance of the original online EBP algorithm for the ranges of (a) learning rate and (b) objective error energy

Fig. 2 depicts the changes in the performance of the system implemented using the proposed method, measured with respect to various values of upper and lower limits. Note that all the performance points in the figure assume a fixed value of 0.005 for (learning) objective error energy. The values in the figure chase the trajectories of the numbers of learning epochs (figure (a)) and verification errors (figure(b)), when the upper and lower limits are set to the combination as depicted. These limits, especially the lower limits, have guaranteed the convergence in the search of learning parameter with the original online EBP. In figure (a), for every upper limit specified, the smallest number of epochs is obtained when the lower limit is 0.5, and the best such number is 214.5 when the upper limit is 2. In figure (b), any particular relationships of the error rates to the upper and lower limits are not found, but the error rates lie in a narrow range between 1.58 % and 1.69 % for all combinations of the upper and lower limits. The best performance, number of epochs 255.2 and error rate 1.58 %, is determined at the upper limit 2 and the lower limit 0.5 in the search.

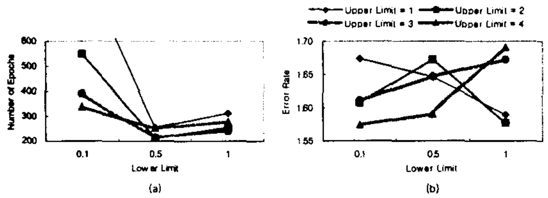

Fig. 2. Performance of the proposed method for various ranges of upper and lower limits: (a) number of epochs and (b) error rate

Fig. 3 compares the best performance of the proposed method with the original online EBP algorithm. Figure (a) compares them with respect to number of epochs and error rate, and figure (b) shows the rates of improvement in the number of epochs. Note that the performance of the proposed method is shown for two different ranges of upper and lower limits: [1..2] and [0.5..2]. In our experiment, the first range achieves no increase in the error rate but the second range increases the error rate by 0.08 % over the best error rate of the original online EBP algorithm. Both ranges are meaningful, however, since they all achieve the error energy, 0.005, imposed as learning objective.

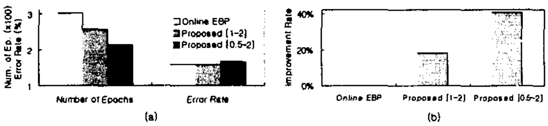

Fig. 3. (a) Performance comparison of the proposed method with the original online EBP algorithm and (b) the rates of improvement in the number of epochs

The proposed method improves the number of epochs by 20 % (approx.) with the first range and by 40 % (approx.) with the second range over the original online EBP algorithm.

Fig. 4 shows the enhanced flexibility of the proposed method over the original online EBP algorithm. For the range [0.1..2] of constant learning rates, the original algorithm shows the best performance of 301.5 for the number of epochs and 1.59 % for error rate, and the worst performance of 1315.3 and 1.88 % respectively. For the range [0.1..2] of lower limits with an upper limit added by 2 to a lower limit (i.e., keeping the length of the range as 2), the proposed method presents the best performance of 209.4 and 1.63 %, respectively, and the worst performance of 566.8 and 1.76 %, respectively, for the number of epochs and error rate. The differential rates between the best and the worst for the number of epochs and error rate are 336 % and 18 %, respectively, with the original online EBP algorithm, and 166 % and 8 %, respectively, with the proposed method. From these numbers, we can say that the flexibility of the proposed method is more than two times of that of the original online EBP algorithm.

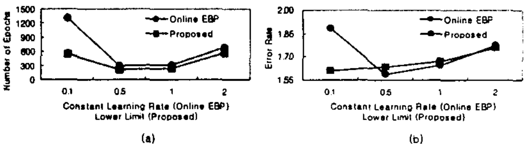

Fig. 4. Enhanced flexibility of the proposed method over the original online EBP algorithm for (a) number of epochs and (b) error rate

5. Conclusion

The results we have presented in this paper are good evidence to verify the more fleet learning and the higher pliability of the proposed method over the original EBP algorithm. In spite of its high capability, the original EBP algorithm suffers from slow learning for learning data and difficulty in selecting an optimal learning rate for working data. To reform these inferiorities, we have suggested the revised version of the EBP algorithm and demonstrated the performance improvement through the experiments of learning on the MLP-based speaker verification system with the Korean speech database. The proposed method would be useful for other MLP-applied signal processing system when the EBP algorithm is adopted for learning MLPs, as well as pattern recognition applications demonstrated in this paper.

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