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EXPERIMENTÁLNÍ ANALÝZA MLP SÍTÍ PRO PREDIKCI POHYBU PLIC PŘI DÝCHÁNÍ

Experimental Analysis of MLP for Lung Respiration Prediction

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Abstract: The paper presents a study and comparison of static feedforward neural network performance for prediction of lung motion. A feedforward neural network with local and global optimization to predict human lung respiration is presented. Applicability of the Levenberg-Marquardt algorithm and the backpropagation learning rule during the batch training are discussed. Sliding window learning for retraining static neural network is applied as a more efficient learning prediction method. Prediction results are presented to demonstrate the effectiveness of the applied neural network method.

Key words: lung tumor motion, prediction, feedforward neural networks.

1. Introduction

Human lung respiration prediction with neural networks is a subject of great interest in medicine due to the possibility of capturing dynamics and structural aspects [1]-[5]. It has relevance in tracking radiation therapy, where treatment devices must adapt to anatomical movement as the patient breathes [1]–[3]. Respiration motion is one of the main problems in radiation therapy. It is due to in case of lung tumors, organs and tumors move according respiration motion. It becomes a complex and non-stationary dynamic process. Some breathing is highly irregular in patients whose pulmonary functions are affected by disease. According to the above, an effective prediction should be able to treat with all respiratory behavior of the patients. Several methods have been developed to model the respiratory motion gated radiation therapy or real time tumor tracking, but their use is still questioned [1]-[5] [7][8]. In this way, artificial neural networks have been applied in time series forecasting in the last two decades. The good ability of the function approximation and strong performance of pattern learning are known by using error backpropagation learning algorithm with feedforward multilayer neural networks called multilayer perceptron (MLP). We used two types of supervised learning algorithms; also known as local optimization and global optimization algorithms. As the local optimization algorithm we used the gradient-descendent rule, which is fast but may tends to learn temporary system behavior (dynamics). The implemented global optimization is the well known Levenberg-Marquardt algorithm . This technique is used in the literature for non-linear least-squares problems. When the solution is far from the correct one, the algorithm behaves as a steepest descent method.

First, we investigate the prediction accuracy of MLP NN trained sample-by-sample by adaptation gradient learning rule derived by backpropagation technique. Second, we use MLP NN trained by L-M algorithm and compare the results.

Furthermore, we investigate the effect on the prediction accuracy when the networks are more properly retrained at every new measured sample for both the sample-by-sample adaptation and also for L-M optimization.

2. Related Works

To achieve such lung prediction several methods have been proposed. Three general approaches have been achieved to predict respiration behavior. Bio-mechanical study of the breathing process is the basic approach [2]-[4]. Other method consists of a respiratory mathematical model using harmonic functions. The most promising method is an approach based on learning algorithms which need to be trained with some patterns observed previously [2]-[4]. The time series of the lung respiration has a quasi-periodic or even chaotic nature and the behavior may vary in time [4]-[5].

In [2] the use of neural network filters is demonstrated to correlate tumor position with external surrogate markers while simultaneously predicting the motion ahead in time; this method shows that adaptive signal processing filters can provide more accurate tumor position estimates than stationary filters when presented with nonstationary breathing motion. In [3], a study on the use of prediction to compensate for system latencies and reduced imaging rate in real-time is presented. It is reported that using prediction improves gated treatment accuracy for systems that have latency of 200 ms or gated, and for systems that have imaging rates of 10 Hz or slower. An analysis of linear versus nonlinear neural network filter for predicting tumor motion ahead in time when the breathing behavior is moderately to extremely irregular is proposed in [4]. Some authors are convinced that deep analysis is still needed [1]

3. Objective

The goal is to investigate the potentials for the prediction accuracy of one millimeter with at least 0.5 second prediction time and to present a more exhaustive study and comparison of static neural network performance for prediction of lung motion.

4. Methodology

Experimental analysis was performed on real respiration data of lung movement. We use real measured data of patient lung movement during respiration in a supine position sampling $1/30$ seconds [5] [9]. Before neural network processing, the noise was filtered and the data were normalized by subtracting the mean and divided by standard deviation of 3.65. Training sets were taken from time series of this data. In sample by sample and L-M optimization were analyzed 2000 samples later of such time series, and a moving window were used to analyze the following 1000 samples according with the size of the window. The testing sets are taken from consequent 1000 samples. It was found that all the predictors had a proper perform reducing the mean absolute error (MAE) and the sum of square errors (SSE). The sample by sample adaptation algorithm with backpropagation learning rule for local optimization was applied. After this first adaptation we applied a sliding window technique in order to improve the adaptation of weights as well. The L-M optimization algorithm was applied and after this we improved the adaptation weights with the sliding window technique as well. We trained every network 100 epochs and the performance goal is achieved. Finally, the results for lung respiration prediction are shown below. Both algorithms, sample by sample and batch optimization, were trained with 5,7 and 10 neurons, with 15, 30 and 60 samples back of the time series and with the corresponding predicting time ahead 15,30 and 60 samples. For every figure, n_r is number of samples back; n_1 means number of neurons and ns means number of prediction ahead.

5. Results

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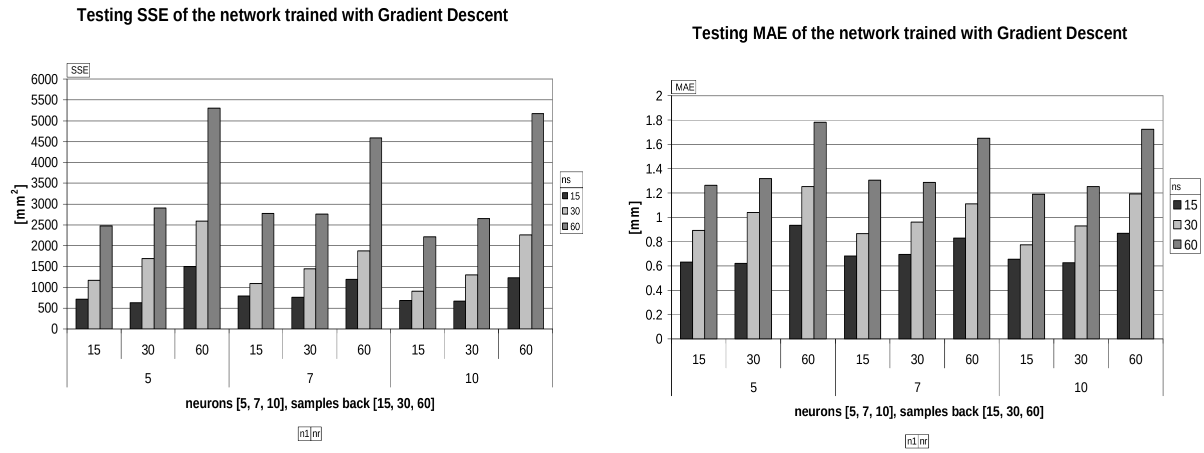

Fig. 1.(Left) figure shows the sum of square error testing performance comparison of the network with gradient descent.(Right) figure shows the mean absolute error testing performance comparison.

With gradient descent the best testing behavior was 15 samples back and 10 neurons for 15, 30 and 60 samples ahead. The testing was performed on respiration data with sliding window algorithm after the weights were updated with gradient descent algorithm. Testing performance comparison of the network trained with gradient descent using sliding window, applying different neurons, samples back, predicting samples are showed in Fig. 2. The size of the moving window was 60 samples. It is moving sample by sample as well.

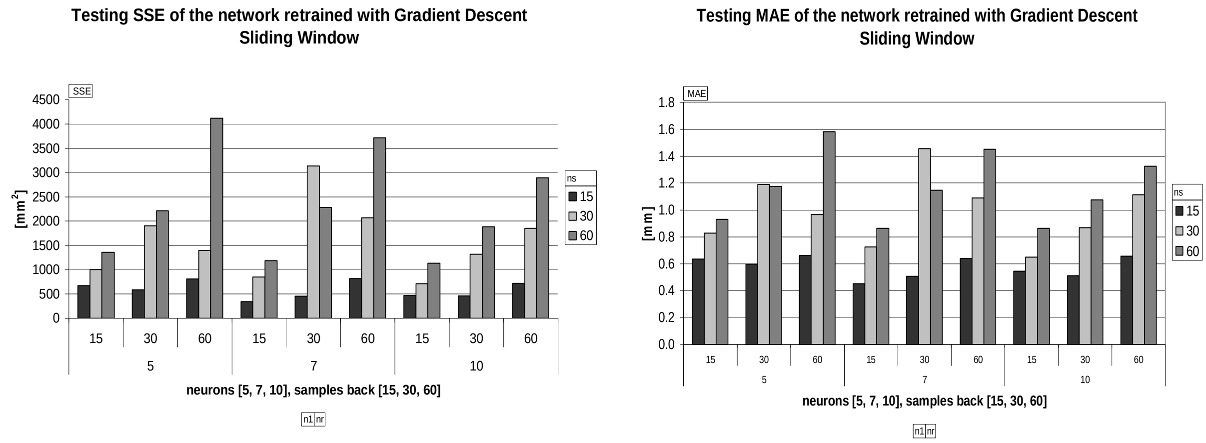

Fig. 2.(Left) figure shows the sum of square error testing performance comparison of the network trained with gradient descent and retrained using gradient descent sliding window.(Right) figure shows the mean absolute error testing performance comparison.

The best training behaviour of the network with moving window was 15 samples back, 5 neurons and 180 samples window size, for 15, 30 and 60 samples ahead.

On the other hand, tests performed on respiration data with Levenberg-Marquard algorithm are shown in Fig. 3. Using L-M algorithm, the best training behavior was 60 samples back and 5 neurons for 15, 30 and 60 samples ahead.

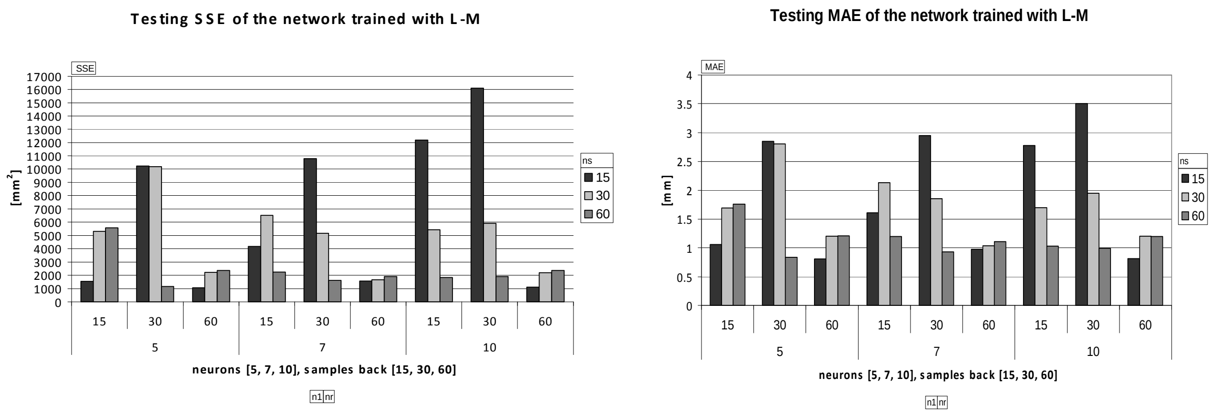

Fig. 3. (Left) figure shows sum of square error testing performance comparison of the network trained with Levenberg-Marquard algorithm. (Right) figure presents the mean absolute error testing performance comparison.

The retraining was performed on respiration data with L-M algorithm after the weights were updated with L-M algorithm. The Network performance comparison with L-M algorithm sliding window, applying different neurons, samples back, predicting samples are shown in Fig. 4. The size of the sliding window was 60 samples moving one by one in the retraining way.

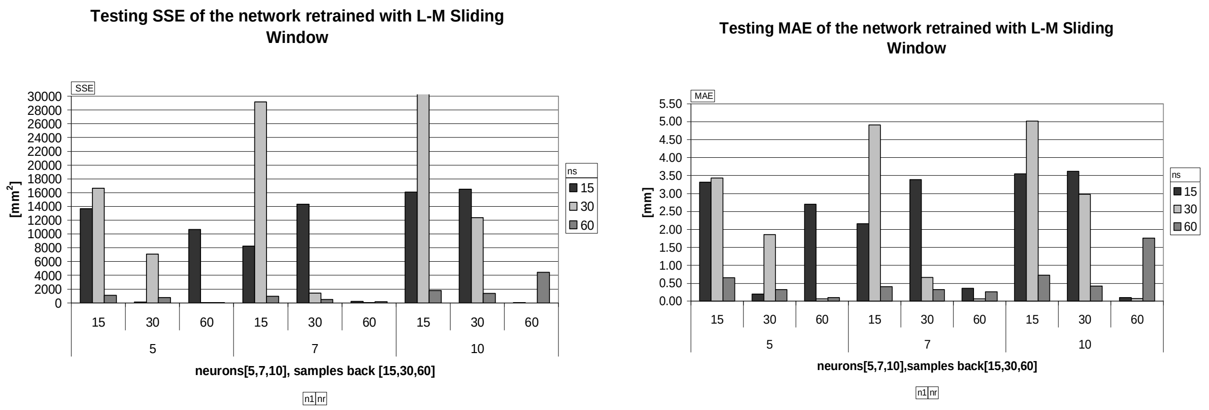

Fig. 4. (Left) figure presents sum of square error testing performance comparison of the network trained with L-M and retrained using L-M sliding window. (Right) figure presents the mean absolute error testing performance comparison.

6. Conclusions

In this paper, we presented a MLP with one hidden layer and its sample by sample adaptation rule and global optimization. Also, we introduced a moving window for every new sample as a retraining method. Then we demonstrated the good converge of the moving window on periodic and highly nonlinear respiration movement time series. Sample by sample adaptation with gradient descent were applied for prediction of real data of lung movement during patient respiration. The problems of local minima and slow converge speed experienced by local optimization traditional learning algorithms are pointed out in this paper. Under this stimulus, a fast and efficient training algorithm for feedforward neural networks with one hidden layer called L-M algorithm was implemented and tested. The sliding window was used to improve the behavior of the accuracy of the training by L-M algorithm. However, we obtained better prediction accuracy with sample by sample adaptation improved with sliding window retraining technique for almost all the prediction testing. In the case of L-M algorithm we obtain much better prediction accuracy for some prediction testing cases where the number of samples back are 60 samples. We realized that L-M algorithm needs to take more inputs from the time series in order to model the whole behavior of the data to predict accuracy. On the other hand, sample by sample adaptation allows predicting accuracy with less number of samples back and less number of neurons. We also realized that the accuracy of the networks implemented to predict time-changing patterns depend on the speed with the network can adapt to this changes. However, regular breathing can be predicted with high accuracy up to 60 samples in advance.

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