Comparative Analysis of Neural Network Training Methods in Real-time Radiotherapy

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ABSTRACT

Background: The motions of body and tumor in some regions such as chest during radiotherapy treatments are one of the major concerns protecting normal tissues against high doses. By using real-time radiotherapy technique, it is possible to increase the accuracy of delivered dose to the tumor region by means of tracing markers on the body of patients.

Objective: This study evaluates the accuracy of some artificial intelligence methods including neural network and those of combination with genetic algorithm as well as particle swarm optimization (PSO) estimating tumor positions in real-time radiotherapy.

Method: One hundred recorded signals of three external markers were used as input data. The signals from 3 markers thorough 10 breathing cycles of a patient treated via a cyber-knife for a lung tumor were used as data input. Then, neural network method and its combination with genetic or PSO algorithms were applied determining the tumor locations using MATLAB© software program.

Results: The accuracies were obtained 0.8%, 12% and 14% in neural network, genetic and particle swarm optimization algorithms, respectively.

Conclusion: The internal target volume (ITV) should be determined based on the applied neural network algorithm on training steps.

Keywords

Real-Time, Radiotherapy, Neural, Network, Error, Genetic, Particle Swarm, Algorithm

Introduction

Radiotherapy is an effective method killing cancer cells or preventing their abnormal growth using high doses of ionizing radiation beams. Therefore, it is important to know the exact locations of tumors in body to deliver maximum dose to the tumor region and to protect surrounding normal tissues against high exposure [1].

In upper parts of body, the usual motions of organs (e.g. chest in breathing cycles or stomach) make difficulties delivering treatment doses exactly to tumor volume [2-4]. This instability in tumor localization not only leads to insufficient dose of tumor volume, but also may cause side effects to the normal tissues. The real-time radiotherapy by cyber-knife systems is one way to determine the exact location of tumor within the body of patients during treatment time [5].

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In real-time radiotherapy, the moment locations of tumor should be recorded continuously by various tracking methods such as wireless sensors, electromagnetic transponders and external/internal markers placed on the patients' body during the treatment time through various mathematical algorithms [6-8]. Thus, a successful treatment strongly depends on the accuracy of applied algorithm as well as the quickness in data accusation.

Neural network algorithm may be used as one of the efficient methods to localize tumors. The input data would be taken from sensor signals on a patients' body. Consequently, the extension of internal tumor volume (ITV) would be affected by the applied training approach and its accuracies in tumor localization.

In this research, first the three important algorithms; neural network, genetic and particle swarm optimizations (PSO) are explained in a real treatment model. Then, the accuracy of the three methods is measured and compared.

Material and Methods

100 recorded signals of three external markers were used as input data. The signals were obtained thorough 10 breathing cycles of a patient by a cyber-knife during a lung tumor treatment time. Ten data signals were used in training of the network before the beginning of treatment. In addition, the signals obtained from an internal implanted marker inside the tumor were used as output data. The samples of input and output data are presented in Table 1.

In order to determine tumor locations, neural network method and its combination with genetic or PSO algorithms were applied training the networks using MATLAB© software program. The Train, Train Using_GA_Fcn, Train Using_PSO_Fcn and MSE instructions in the program were used as the main functions in neural network, genetic and PSO algorithms as well as their mean squared error estimations, respectively.

Table 1: Example of three used dimensional coordination of output and input data obtained from external and internal markers.

No. Data	First Marker			Second Marker			Third Marker			Internal Marker		
	X	Y	Z	X	Y	Z	X	Y	Z	X	Y	Z
1	0.29	0.39	-0.25	0.53	0.69	-0.06	0.55	0.48	0.06	-0.09	-2.15	-5.43
2	0.61	0.73	-0.52	0.48	0.62	-0.16	0.55	0.37	0.15	-0.03	-2.21	-5.71
3	0.22	0.33	-0.23	0.34	0.53	-0.04	0.20	0.32	0.10	-0.23	2.34	-5.90
4	-0.31	-0.40	0.11	-0.33	-0.30	-0.10	-0.04	-0.10	-0.11	-0.30	-2.30	-6.30
5	-0.30	-0.40	0.21	-0.33	-0.44	-0.11	-0.12	-0.10	-0.13	-0.33	-2.33	-6.20
6	0.30	0.40	-0.13	0.12	0.30	0.10	0.02	0.03	0.01	-0.31	-2.01	-6.10
7	0.20	-0.42	0.24	-0.40	-0.42	-0.03	-0.30	-3.33	-0.12	-0.40	-2.10	-6.31
8	0.50	-0.73	0.31	-0.42	-0.60	0.10	-0.34	-0.34	0.13	-0.44	-2.14	-6.34
9	-0.30	-0.61	0.24	-0.40	-0.49	0.11	-0.20	-0.21	-0.02	-0.40	-2.13	-6.33
10	0.20	0.10	-0.05	0.08	-0.03	0.23	-0.01	-0.04	0.10	-0.44	-2.10	-6.31

Results and Discussion

Neural Network Algorithm

Figure 1 shows an example of tracking a tumor locations obtained from neural network algorithm. The locations follow the coordinate values of the three external markers presented in Table 1. In fact, these displacements in location of markers are compatible with the contraction and expansion of lung tissue during ten breathing cycles in horizontal and vertical directions.

Figure 2 presents the mean square error (MSE) values on different training steps of network. As it is shown, one of the interrupted conditions has been realized and confirmed after 102 times of training to neurons obtaining the MSE value by less than 10^{-5} value.

Figure 3 shows the simulated real outputs in comparison with the train outputs. As it is demostrated, a perfect compatibility between real, training and test can be observed in all data. Figure 4 shows the regression curves of training data (the right curve) and those of test (the left curve) against the target output obtained from neural network algorithm. R values were calculated 0.99999 and 0.99953 for the training and test data, respectively.

Genetic Algorithm

Figure 5 displays the real outputs versus the training and test data obtained from genetic algorithm on training steps. In spite of the compatibility between real, training and test in all data, low accuracy in marker tracking can be observed in Figure 5. The related regression curves are presented in Figure 6. The derived R values of 0.79661 and 0.88542 for training and test data respectively indicate that the accuracy of method would be less than that of neural network algorithm.

Particle Swarm Optimization

Figure 7 shows the real outputs versus the training and test data obtained from PSO meth-

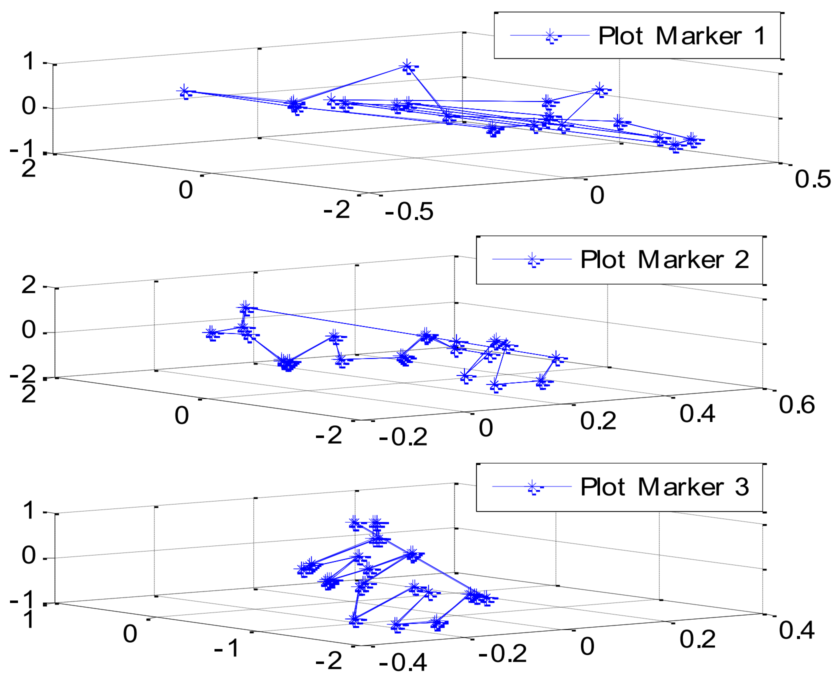

Figure 1: Tracking the variations in three-dimensional localization of the three external markers

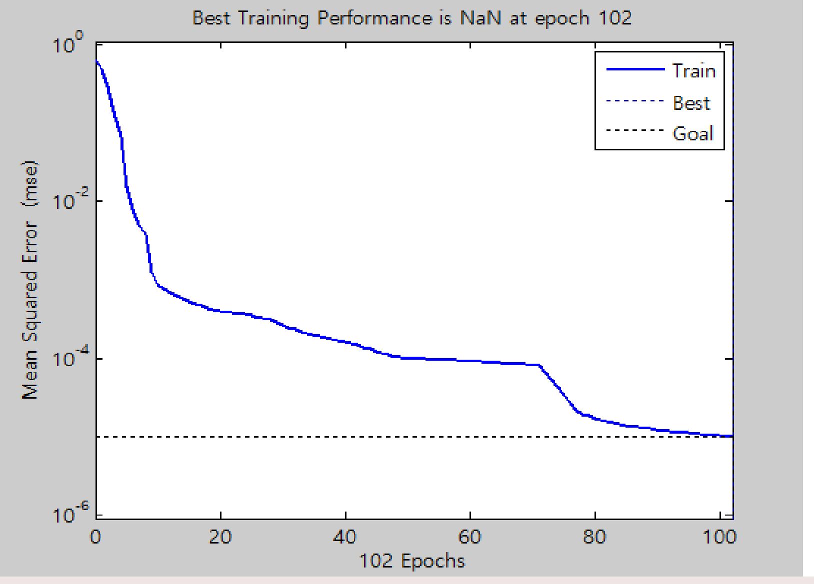

Figure 2: Mean Squared Error values versus 102 epochs of training steps in neural network.

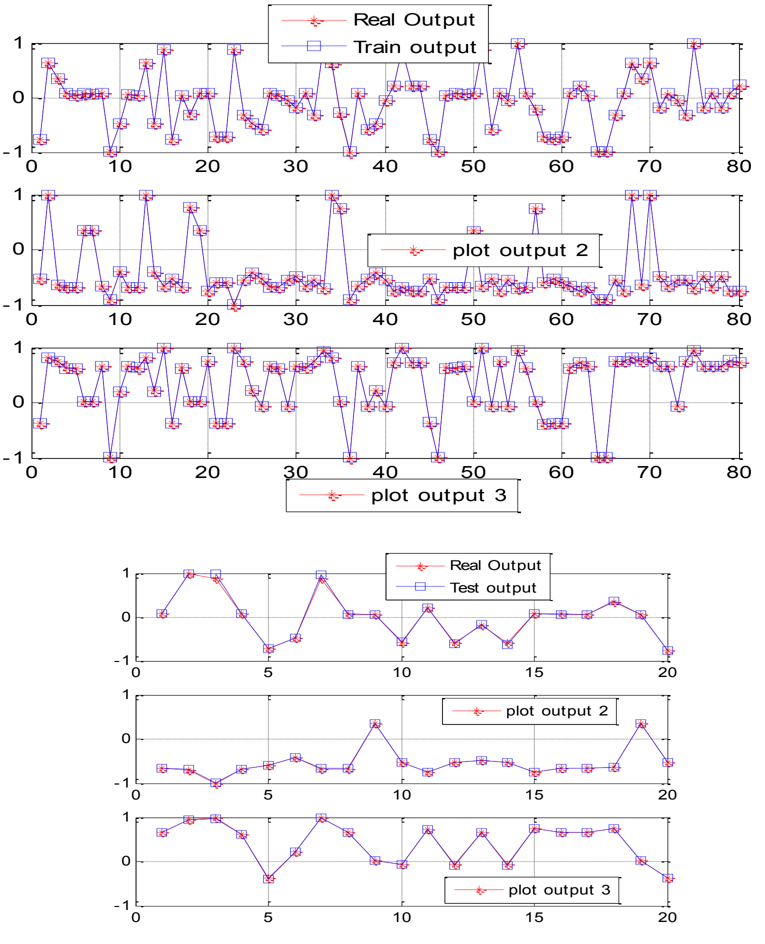

Figure 3: Comparison of test and train outputs with the real outputs in neural network algorithm

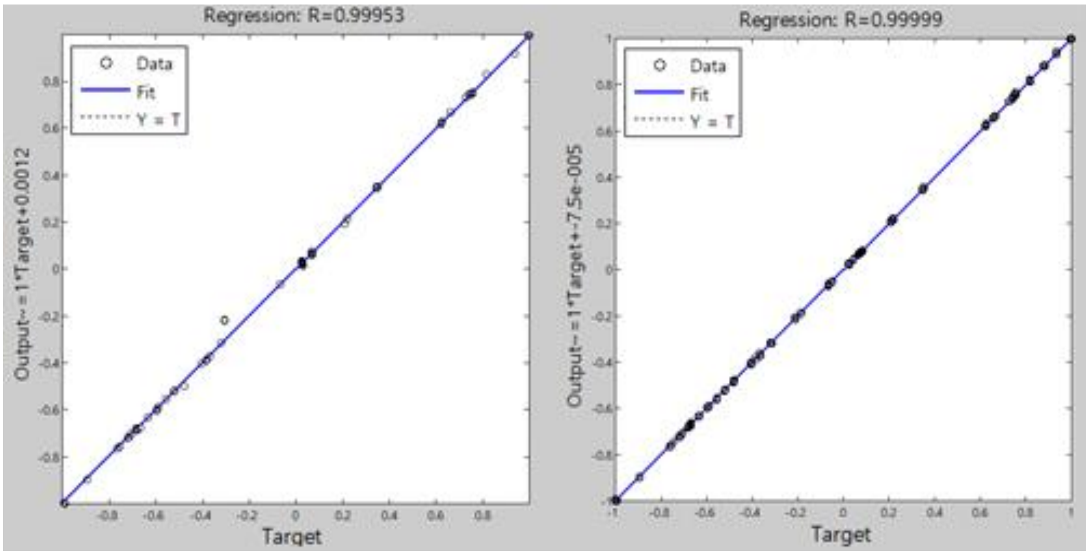

Figure 4: The regression curve of training output (right), and of test output (left) in neural network algorithm

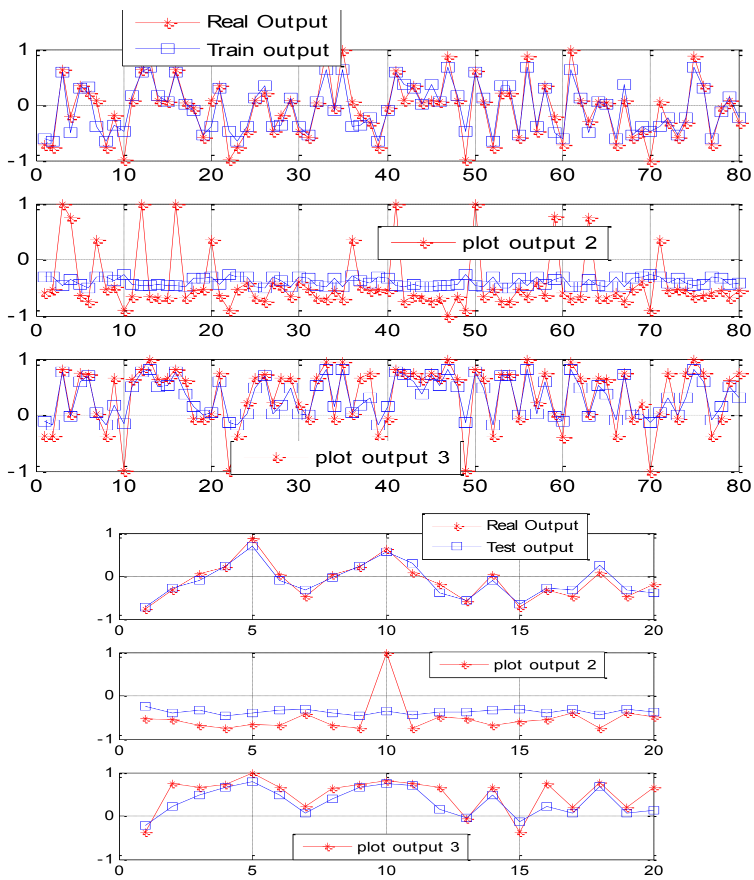

Figure 5: Comparison of test and train outputs with the real outputs in genetic algorithm

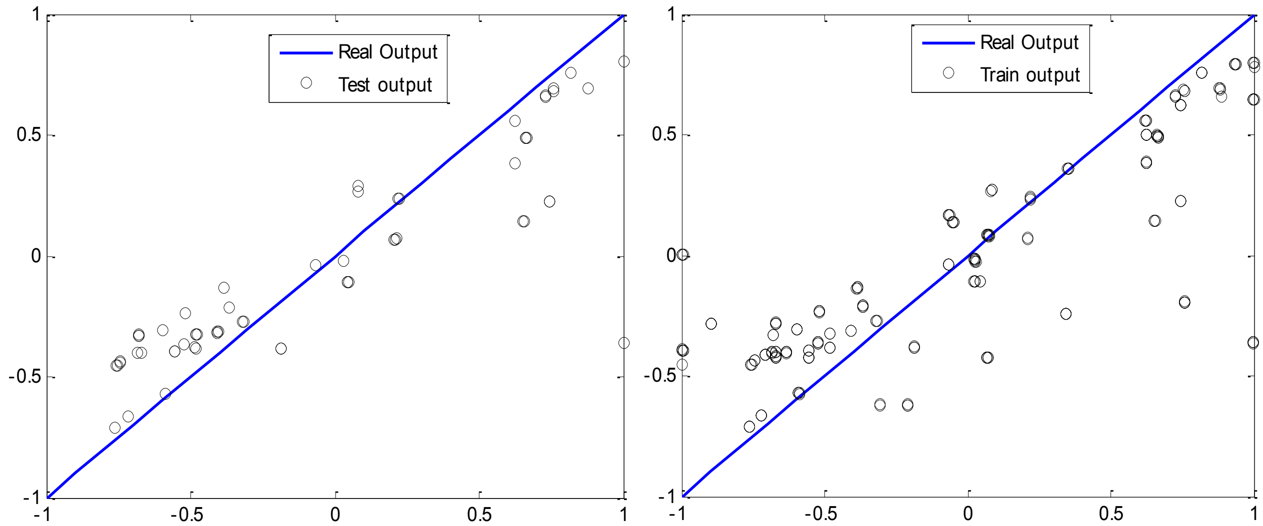

Figure 6: The regression curve of training output (right), and of test output (left) in genetic algorithm

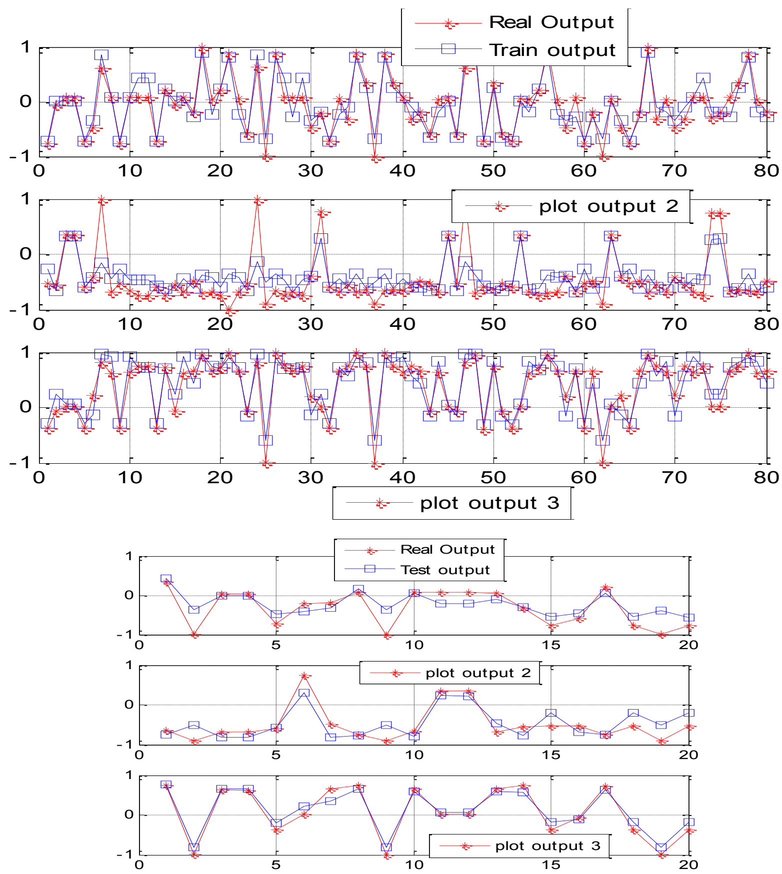

Figure 7: Comparison of test and train outputs with the real outputs in PSO algorithm

od on training step. The R values of 0.91487 and 0.91373 indicate a rather better degree of compatibility with regard to the genetic algorithm obtained from real, training and test data in this algorithm. However, the comparison between training and test data demonstrates that the accuracy of method would be still less than those of neural network algorithm.

Comparisons of Training Approaches

Table 2 presents the results of the average mean square error (MSE) as well as the accuracy of test and training steps of the three algorithms. The average error values of 0.8%, 12% and 14% respectively in neural network, genetic algorithm and PSO method indicate that the neural network algorithm generally give the best estimation of the tumor locations in real-time radiotherapy.

Therefore, if only the neural network algorithm is used on training step, it can be assumed that the internal target volume (ITV) has exactly covered the clinical target volume (CTV). Thus, a minimum expansion of ITV can be considered in treatment planning of the tumor.

However, if the combinations of neural network with genetic or PSO algorithms are used on training steps, it is necessary to extent ITV zone compensating the intrinsic errors in related tumor localizations. The value of extension would evidently depend on the number of inputs on training and test steps.

Conclusion

Various training algorithms including neural network, genetic and POS were compared in the localization of tumors within moving organs in real-time radiotherapy. The results indicate that neural network algorithm can precisely trace the location of tumor, and the combination of training steps with other algorithms such as genetic and POS cannot improve the accuracy. Consequently, the ITV strongly depends on the applied neural network algorithm on training steps and must be extended in genetic and POS algorithms.

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Conflict of Interest

None

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Table 2: Average mean square errors (MSE) and the accuracy of test and training steps of the three algorithms

Algorithm	MES of training (MSE tr)	Averaged error of training (MSE tr_Er)	MES of test (MSE ts)	Averaged error of test (MSE ts_Er)
Neural Network	9.88E-6	0.1572%	3.09E-4	0.8785%
Genetic	0.1233	12.5214%	0.0211	14.1342%
PSO	0.0513	11.3281	0.0148	11.8433%

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