Application of deep neural networks for bone-suppressed digital radiography

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1. Introduction

Chest radiograph represents the three-dimensional object as a two-dimensional image, resulting in overlapping of anatomical information. As a result, the visibility of the lesion is deteriorated. In order to overcome this problem, there are dual-shot dual-energy imaging [1], single-shot dual-energy imaging [2], computed tomography (CT), digital tomosynthesis (DTS) [3] and artificial neural network (ANN) [4].

Each technique has its own problems. The double-shot dual-energy imaging is sensitive to the motion artifacts because of the time interval between two successive exposures [1]. Single-shot dual-energy imaging solves the motion artifact problem by acquiring images in only one shot. But the contrast-to-noise ratio (CNR) is low due to poor performance of the spectral energy separation [2]. CT and DTS require complicated equipment and high radiation exposure. The ANN uses a shallow network with one hidden layer [4]. Thus, training performance would be worse than that of the deep networks with multiple hidden layers [5].

In the work, we propose a bone-suppressed imaging technique using a deep neural network (DNN). This technique acquires a bone-suppressed image at a single shot through the trained DNN. Therefore, it can overcome the problems such as the motion artifact and high exposure dose. The training of DNN requires a chest radiograph and bone-enhanced image.

The parameter values of DNN affect the training speed and the results. So we need to optimize the parameter values. In this study, we perform a study on the parameter optimization of bone-suppressed imaging technique using the DNN.

2. Method

We implement the DNN using the Tensorflow (Google), a commercial artificial intelligence network implementation platform. Bone-enhanced image is obtained by training chest radiograph using the DNN. We can obtain a bone suppressed image by using the weighted log-subtraction of the resulting image and the chest radiograph.

2.1 Deep neural network (DNN)

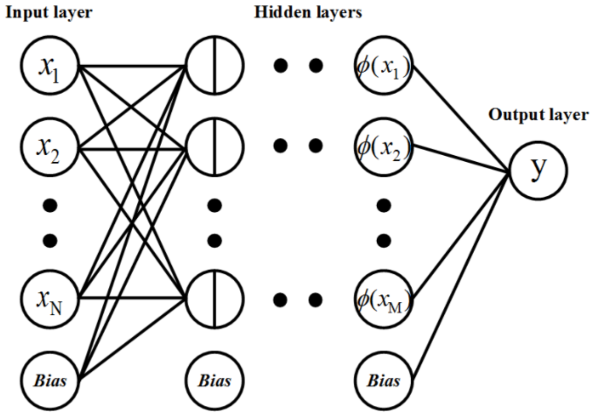

Fig 1. The concept of the DNN.

Fig 1 shows the structure of DNN used in this study. The DNN consists of three layers: input, hidden, and output layers. Each layer includes multiple nodes. Additionally, the input and hidden layers contain the bias nodes. The output node of the DNN is determined by the activation function:

$$y(x,w) = f\left(\textstyle\sum_j w_j\,\phi_j(x)\right), \quad (1)$$

where x is input signal, w is the weight, $\phi(x)$ is the output from hidden layer, f is the activation function.

The training of the neural network calculates the output signal through feed-forward, as shown in Eq. (1). To reduce the difference between the output and the label signal, the weights are updated until convergence through the gradient descent method for the error, e between the output and the label signal:

$$W^{(i)} = W^{(i-1)} - \eta \cdot \frac{\partial e^{(i-1)}}{\partial W^{(i-1)}}, \quad (2)$$

where the weights of the current state, $W^{(i)}$, are obtained using $e^{(i-1)}$ and $W^{(i-1)}$ in the previous state. η is the learning rate and affects the learning speed.

2.2 Rectified linear unit (ReLU)

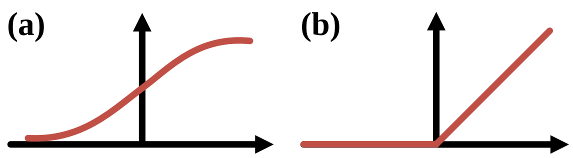

Fig 2. (a)Sigmoid, (b) ReLU function.

$$f(x) = \frac{1}{1+e^{x}} \tag{3}$$

Eq. (3) represents a sigmoid function, where x is the input value.

$$f(x) = \begin{cases} x, x \geq 0 \\ 0, x < 0 \end{cases} \tag{4}$$

Eq. (4) represents a ReLU function.

When the sigmoid function is used as the activation function in the DNN, as shown in Fig 2(a), a vanishing gradient problem occurs. When calculating the variation of weighting factor of DNN, we use the products of the differential activation function values. When using the sigmoid function in training, the differential value of the activation function is between 0 and 1. Therefore, the variation of weighting factor in the deeper layer of the neural network becomes 0, and training could not done.

To solve this problem, we use the ReLU function as shown in Fig 2(b). The differential value of ReLU is always 1, which can alleviate the vanishing gradient problem. Also, the value of the ReLU function becomes 0 according to each input value. As a result, the activated nodes can be changed, and training can be performed in many DNN structures, which improves training. [6]

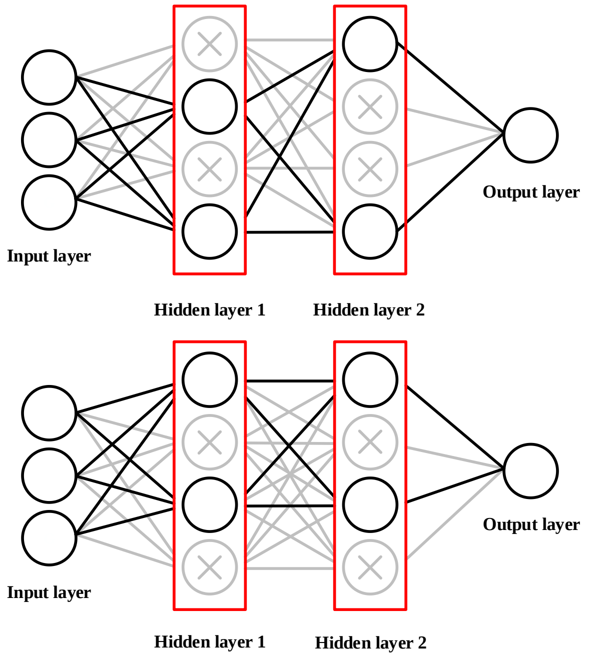

Fig 3. Structure of neural network using dropout. During training, hidden nodes in each hidden layer are dropped at the constant probability.

2.3 Dropout

To prevent overfitting of neural networks, we employ the dropout method. During training, the error about the training data should be kept low. However the generalization ability of the neural network fails. This is called overfitting.

To solve this problem, there is a method of training using various data or structures of various neural networks. Using the dropout, as shown in Fig 3, it is possible to obtain the training effect by various neural network structure, and overfitting can be mitigated. [7]

3. Performing training

3.1 Data preparation

In this study, we prepare chest radiographs and bone enhanced images obtained by dual energy imaging (DEI) from three patients as shown in Fig 4. The projection images are acquired from a commercial chest radiography system using a dual energy imaging function (Definum 8000, GE healthcare, USA). The projection image size is 2022×2022 and the pixel size is 0.195mm.

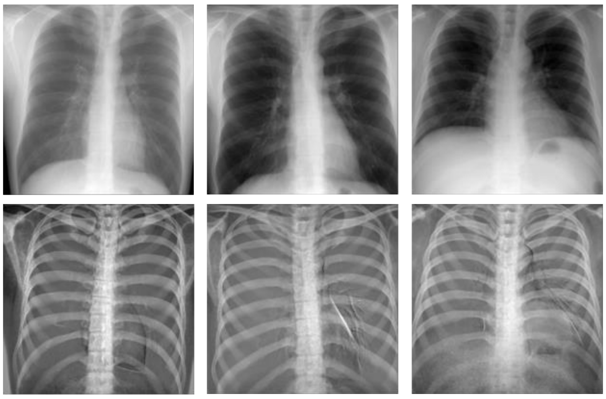

Fig 4. The upper row shows chest radiographs and lower shows bone enhanced images.

3.2 DNN parameter

To improve performance of DNN, we optimize DNN parameters.

The DNN parameters include the number of hidden layers, the number of hidden nodes in each hidden layer, the number of batches (the number of inputs used in learning), and the learning rate.

3. Preliminary Result

Table 1. DNN simulation parameters

Description	***Value***
Hidden layer	5
Hidden node / (1 layer)	200
Training set	13500
Validation set	4500
Batch	15
Learning rate	0.001
Epoch	30000
Calculation time	120000 seconds

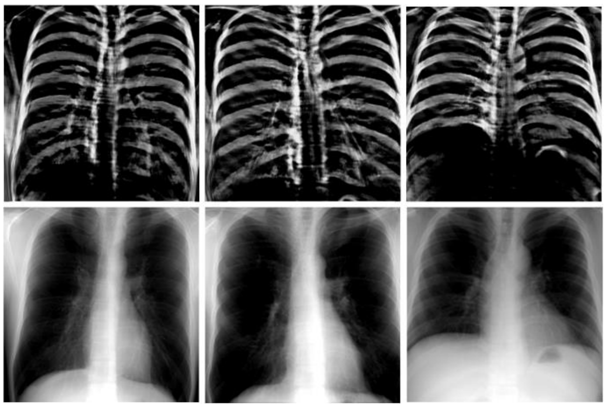

Fig 5. Bone enhanced images and bone suppressed images are obtained by trained DNN.

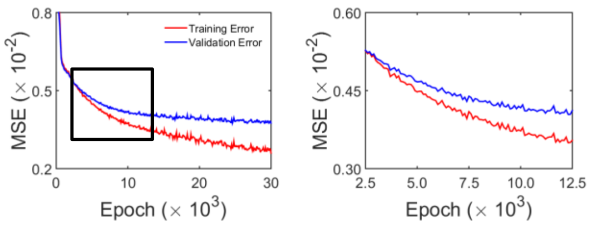

Fig 6. Training, validation Error graph

DNN training was performed using the GPU(GeForce GXT 980), and Fig. 5 is a bone-enhanced image obtained under the condition of Table 1. Fig 6 shows the error graph for the training set and the validation set. After the epoch of 5000, it can be confirmed that the slope of the validation error becomes gentle, and it is assumed that overfitting will occur at this epoch.

4. Further Study

Each parameter is closely related to the DNN learning ability and speed. Therefore, we should optimize the parameter value by quantitatively comparing the result obtained by simulating with various conditions.

The goal of the study is to obtain bone-suppressed images. To do this, we will implement a subtraction algorithm and quantitatively evaluate the acquired bone-suppressed image.

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