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Initial Investigation of Software-Based Bone-Suppressed Imaging

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1. Introduction

Chest radiography is the most widely used imaging modality in medicine. However, the diagnostic performance of chest radiography is deteriorated by the anatomical background of the patient. So, dual energy imaging (DEI) has recently been emerged and demonstrated an improved. However, the typical DEI requires more than two projections, hence causing additional patient dose. The motion artifact is another concern in the DEI [1].

In this study, we investigate DEI-like bone-suppressed imaging based on the post processing of a single radiograph. To obtain bone-only images, we use the artificial neural network (ANN) method with the error backpropagation-based machine learning approach [2].

2. Methods and Results

2.1 Artificial neural network

The ANN is a mathematical model that aims to mimic the human brain to decide specific purpose [3]. ANNs basically simplify the human brain as a connected web, which is composed of neurons and synapses as shown in Fig 1. The ANN is configured with nodes and weighting factors which correspond the neurons and synapses, respectively. Each node includes decision functions. The most intuitive decision function used in the ANN is the simple thresholding, which means that each node decides only “true and false”. Although more advanced decision functions, such as sigmoidal function and hyperbolic

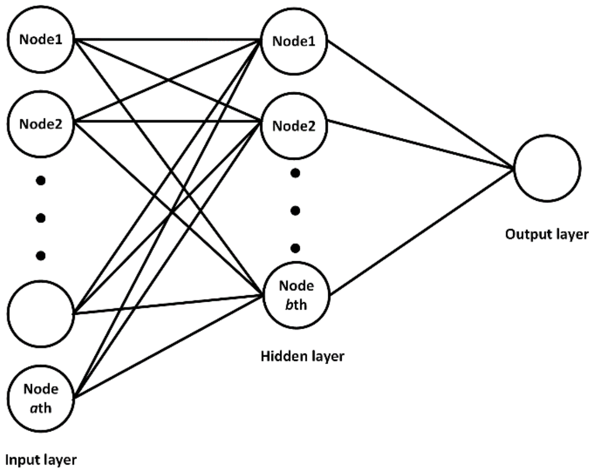

Fig. 1. The concept of the ANN algorithm.

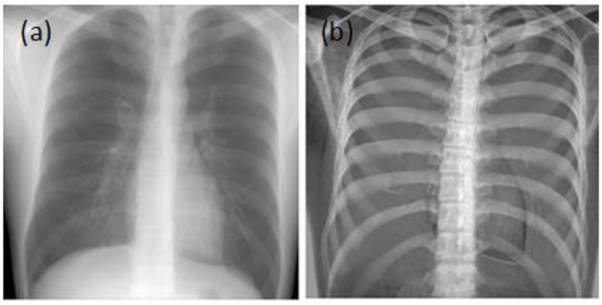

Fig 2. (a) Input chest radiograph and (b) Bone enhanced dual energy radiograph.

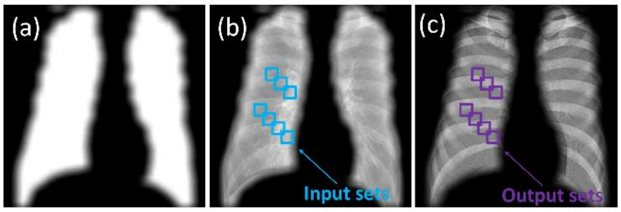

Fig 3. Input data preparation: lung mask (a), lung mask applied input projection (b), and output projection (c).

tangential, are available the basic concept is still valid. The weighting factors assign weightings to the output signal of each node. Therefore, the input signal to the next layered node is determined by the combination of output signal from previous nodes and weighting factors. Finally, the node at the last layer generates the output signal using the combination of previous layers.

2.2 Data preparation

To establish the accurate algorithm to acquire bone-suppressed chest radiograph, the correctly determined learning set is essential. In this study, we prepare a chest radiograph and a bone-enhanced dual energy radiograph for the same patient as shown in Fig 2. The projection image is acquired from a commercial chest radiography system (Definum 8000, GE healthcare, USA), which employs dual energy imaging function. The projection images are composed of 2022 $\times$ 2022 pixels with a pixel size of 0.195 mm. Bone sections in the chest radiograph is divided into subregions for learning. Using the lung mask, as shown in Fig 3(a), we extract rib bones.

2.3 Bone suppression algorithm

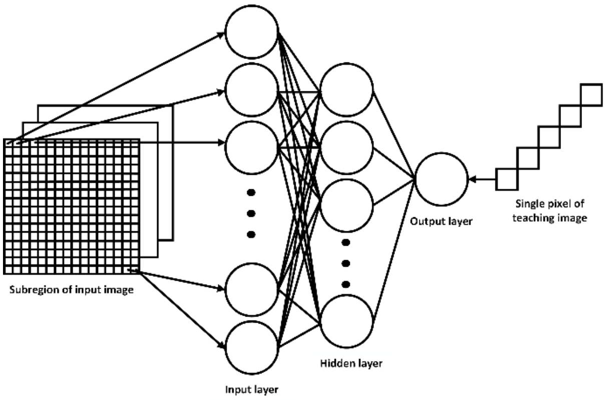

Fig 4. Schematic illustration of bone suppression procedure by using the ANN.

The inputs of the ANN are the pixel values in a subregion R_s extracted from an input image. The bone-only image after learning is given by [4]

$$f(x,y) = ANN(\vec{I}_{x,y}) \tag{1}$$

where $\vec{I}_{x,y}$ is the set of patches for learning:

$$\vec{I}_{x,y} = \{r(x-i, y-j) \mid i, j \in R_s\} \tag{2}$$

$f(x,y)$ is an assumption for a teaching value. $ANN\{\cdots\}$ implies the ANN learning process. $r(x,y)$ is a normalized pixel value at the input image.

The output of the b th unit in the hidden layer is determined by the weighted summation of the a th units of the input layer:

$$O_b^H = f_s\{\sum_a w_{ab}^H \cdot I_a - w_{0b}^H\}, \tag{3}$$

where w_{ab}^H is the weighting factor between the a th unit of the input layer and the b th unit of the hidden layer and w_{0b}^H is a bias of the b th unit in the hidden layer. The decision function is in this study given by

$$f_s(u) = \frac{1-e^{-2x}}{1+e^{-2x}}. \tag{4}$$

Similarly, the output of the unit in the output layer is given by

$$f(x,y) = f_L\{\sum_a w_a^O \cdot O_a^H - w_0^O\} \tag{5}$$

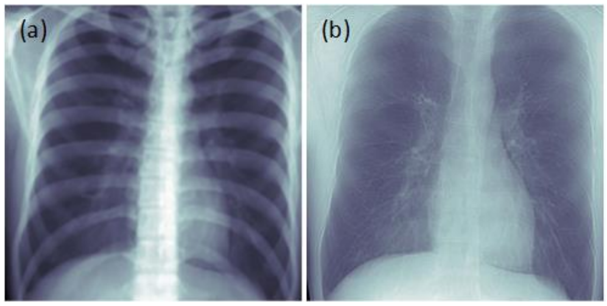

Fig 5. Resultant bone enhanced image (a), and tissue enhanced image (b).

where w_a^O is the weighting factor between the a th unit of the hidden layer and the unit of the output layer, w_0^O is a bias of the unit in the output layer. The decision function is

$$f_L(u) = a \cdot u + 0.5\,. \tag{6}$$

3. Preliminary Results

For the preliminary results, we apply the ANN algorithm to a single patient. The number of ROIs taken from the test sets is 5000 and number of hidden nodes is 3. The machine learning process takes about 30 days to converge by using a 2.4 GHz single-core CPU and 64 GB memory. Fig 5 shows the final learning images. Figure 5(a) is the bone-only image obtained from the ANN algorithm and Fig 5(b) is the bone-suppressed image by using the log-subtraction method with the bone-only image and the original image. We can observe the successful results compared with the DEI images, as shown in Fig 5(b). However, the rip edge regions are study is limited because we used only a single patient. If we can use many patient data, we can have a better result.

4. Further Study

The computational load of learning process of the ANN is too heavy for a practical implementation because we use the gradient descent method for the error backpropagation. We will use a more advanced error propagation method for the learning process. With an improved speed, we will perform multiple patient cases and present quantitative evaluation results.

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