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Anaysis of Idiopathic interstitial Pneumonia by Self Organization Map on High-resolution Computed Tomography Images

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Abstract ***In classifying the idiopathic interstitial pneumonias (IIPs), interpretation of features on high-resolution computed tomography (HRCT) image is effective. However, image patterns of IIPs on HRCT images have so much variety, that the classifying problem is difficult. The purpose of our study is to develop a diagnosis support system for classification of those HRCT images using a Kohonen's self-organizing map (SOM). Our system classify the input HRCT image as 4 IIP classes, that is, Consolidation, Ground-Grass, Honeycomb, and Reticular classes.***

Keyword: Computer Aided Diagnosis, Distributed Lung Disease, Self-Organization map

1 Introduction

In the field of diagnosis using medical imaging, the diagnosis quality is affected by ability of each doctor, so that keeping the quality of diagnosis with objectivity is difficult task. Especially, since the diffuse lung disease, which is treated in this paper, has large variety, the diagnosis is influenced by each doctor's skill and expertise, and plural doctors should make diagnosis for one patient. However, the burden of doctor may become large. Thus, the diagnosis aid system using computer is desired for objective diagnosis in these decades. In this study, we try to construct a computer diagnosis aid using Kohonen's self-organizing map (SOM) algorithm [1][2], and to examine classifying several image data. In the field of artificial neural networks, the SOM algorithm is a kind of an unsupervised learning. In the SOM, several relationship among high-dimensional input data, such that images, sounds and so on, are embedded into a 2-dimensional lattice structure called "map". In the embedding process, similarity between input data is used for assigning the data, and similar data is inclined to assign in near place in the map.

Hence, we can easy to grasp the relationship between data by seeing the map, which describe the similarities among high-dimensional data, and we consider the map as a good supporting tool for making a objective diagnosis. Our purpose is to develop a system for diagnosis doctor to indicate information to distinguish the input image. Several classification method supplies only distinguished result, however, the SOM supply the information about not only cluster to which the input is belongs, but also similarities among other clusters on the map. Hence, we consider it is better to adopt the SOM for supporting diagnosis doctors.

We developed a computerized aided diagnosis (CAD) system for classifying diffuse lung disease, which called idiopathic interstitial pneumonia (IIP). Our CAD system classify the part of high resolution CT (HRCT) images of patients into following four classes, that is, Consolidation, Ground-Grass, Honeycomb, and Reticular. Those lesion is spread in lung area, and have a lot of image patterns. Figure 1. shows a example of each CT image. The top row shows a axial overview of CT image, and bottom row shows magnifications of each lesion.

2 Method

2.1 Input Vector

In usual, the HRCT image consists of 512×512 pixels. However, the image includes not only lung with disease, but also another anatomies. Hence, in our system, we assumed an input image was a part of HRCT image called "region of interest (ROI)" , which was segmented by a doctor, and the size of ROI is configured as 32×32 pixels.

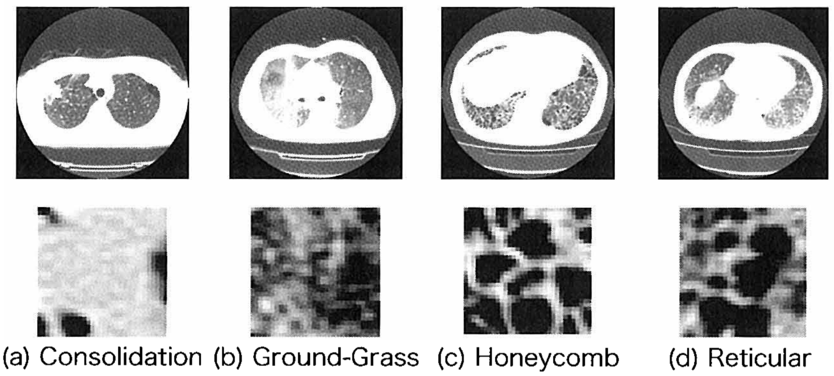

Figure 1: Typical CT images of diffuse lung diseases: The top row shows each overview, and bottom shows magnified part (ROI) of each lesion. From (a) to (d) represents "Consolidation", "Ground-Grass", "Honeycomb", and "Reticular" image respectively.

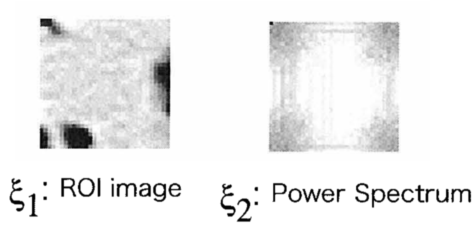

Figure 2: Input features: $\boldsymbol{\xi}_1$ shows ROI with moving averaged. This figure shows an example of consolidation case. $\boldsymbol{\xi}_2$ shows the power spectrum of the ROI image.

To extracting the feature without reducing information of ROI as possible, we adopted each pixel in ROI as an element of a vector, so that the ROI image could be regarded as the 1024 dimensional vector $\boldsymbol{\xi}_1$. To reduce the effect of translation movement of image, we applied moving average filter to the $\boldsymbol{\xi}_1$.

Moreover, we introduce a power spectrum $\boldsymbol{\xi}_2$ of the ROI image $\boldsymbol{\xi}_1$ by use of discrete Fourier transform. The power spectrum of a image includes information about spatial frequency.

Then, we use these two kinds of vectors as input, so that the input vector can be described as $\boldsymbol{\xi} = \{\boldsymbol{\xi}_1, \lambda\boldsymbol{\xi}_2\}$, where λ means efficacy of the power spectrum. Each vector $\boldsymbol{\xi}_1$ and $\boldsymbol{\xi}_2$ includes same information, however, the expression is different. Thus, the similarity between data becomes different, in other words, we introduce another measure.

2.2 The SOM algorithm

To visualize the relationships of the data, we applied the Kohonen's SOM In the field of artificial neural networks, the SOM is regarded as a kind of unsupervised learning method. In the SOM, each datum was described as a point in a two (or three)-dimensional lattice, called as map, and each datum was ordered by similarities against other data, so that similar data was arranged near points in the map. Hence, in the meaning of similarity, we could see the relationships of the high-dimensional input data on the two-dimensional map.

We use two dimensional map which consists of neuron-like units, and we describe each element, which called as node, as $\{n_i\}$ where i means the location index in the map. Each node n_i has an attribute called a reference vector $\boldsymbol{m}_i$. The reference vector has the same dimension as that of the input vector, so that the reference vector means the preferred input of the attached node.

The SOM algorithm is very simple. We assumed that we could prepare the training input vector sets $\{\boldsymbol{x}_p\}_{p=1\cdots N}$, and each reference vector $\boldsymbol{m}_i$ is scattered into the input space randomly in the initial state of the map.

At first, we should select a input vector $\boldsymbol{x}_p$ from the collection of training sets. Then, we select a node which has the nearest reference vector to the input $\boldsymbol{x}_p$ and we call the node as "winner node" which have index c:

$$\boldsymbol{m}_c = \mathrm{argmin}_i \; D(\boldsymbol{x}_p, \boldsymbol{m}_i), \qquad (1)$$

where the function $D(\boldsymbol{x}_p, \boldsymbol{m}_i)$ means a distance between input $\boldsymbol{x}_p$ and reference vector $\boldsymbol{m}_i$. In our system, we adopted Euclidean distance as $D(\boldsymbol{x}_p, \boldsymbol{m}_i)$:

$$D(\boldsymbol{x}_p, \boldsymbol{m}_i) = \sqrt{\sum_q (x_{pq} - m_{iq})^2}, \qquad (2)$$

where q means the index of elements in vectors.

After selecting winner-node, we update the reference vectors of the winner node and its neighbours as following:

$$\boldsymbol{m}_j^{t+1} = \boldsymbol{m}_j^t + \varepsilon(t)\, h(\boldsymbol{r}_c, \boldsymbol{r}_j)\, (\boldsymbol{x}_p - \boldsymbol{m}_j), \qquad (3)$$

where $\varepsilon(t)$ means learning efficacy, $h(\cdot,\cdot)$ means neighborhood function between winner-node c and update-node j, that is,

$$h(\boldsymbol{r}_c, \boldsymbol{r}_j) = \frac{1}{Z} \exp(-\beta D(\boldsymbol{r}_c, \boldsymbol{r}_j)), \qquad (4)$$

where $\boldsymbol{r}_c$ and $\boldsymbol{r}_j$ means the locations of winner node n_c and updating node n_j on the 2-dimensional map and $D(\boldsymbol{r}_c, \boldsymbol{r}_j)$ means the Euclidean distance. The coefficient β controls the efficacy of neighborhood function, that is, the larger β is set, the further the effect of the winner node in equation (3) is reached. Z is a normalize factor

$$Z = \int_{-\infty}^{+\infty} \exp(-\beta|x|)dx. \qquad (5)$$

In the SOM algorithm, the winner selecting process and the update reference vector process would be carried out alternatively for whole training input data with several epochs. In our system, we adopted the learning efficacy $\varepsilon(t)$ as a monotonic decreasing function for the update time t, so that our SOM algorithm would be converge.

2.3 IIP Classification

The SOM algorithm only decides reference vectors of each node, therefore each node has no label for classification. Thus, when we develop a classifying application using the SOM system, classification labels for each node are required. For such need, several implementations for SOM are proposed, that is, perceptron (counter propagation network) or k-means method are used for the labeling[3]. Hence, we applied k-means method, which is a kind of clustering algorithm to classify the SOM output since it is the most simple method. In the k-means method, we assume the input patterns have several clusters.

1. We scattered K clusters, which are denoted as $C_1 \cdots C_K$, onto the input dimension, and each cluster center $\boldsymbol{u}_k$ is located at the average of training input for each disease class, that is, Consolidation, Ground-Grass, Honeycomb, and Reticular.
2. We labeled each map node n_i as the class C_k, which has the minimum distance to the reference vector $\boldsymbol{m}_i$.

   $$n_i \in C_k \ \text{ if } \ D(\boldsymbol{m}_i, \boldsymbol{u}_k) = \min_j D(\boldsymbol{m}_j, \boldsymbol{u}_k) \qquad (6)$$

3. We calculated the center of each cluster as the average of the reference vectors which belongs to the class C_k.

   $$\nu_k = \{n_j \in C_k \ \text{ for all } \ j\}, \ N_k = \#\nu_k$$
   $$\boldsymbol{u}_k = \frac{1}{N_k} \sum_{j \in \nu_k} \boldsymbol{m}_j \qquad (7)$$

4. We iterated above 2.~ 3. processes alternately until cluster centers are converged

3 Experiment

In this study, we evaluated the system with 80 HRCT images (20: Consolidation, 20: Ground-Grass, 20: Honeycomb, and 20: Reticular). The acquisition parameters of those HRCT images were: 512 x 512 pixels, 0.352 mm pixel size, and 2 mm slice thickness.

4 Results

Figure 3 shows the result of the SOM with k-means method. The consolidation cluster and the honeycomb cluster on the map are arranged furthest places. And the reticular cluster and ground-grass cluster are located between these clusters. Thus, we can see the similarities among lesion images, and we consider that showing these relationships would be helpful for the diagnosis of diffuse lung disease.

Moreover, for quantitative evaluation, we investigate the pattern classification ability of our system. In the experiment using 80 ROI images, average classification error rates of 83.4 % (67/80) was obtained. Table1 shows the detail classification result. In the consolidation patterns, 1 case was classified as reticular. In the ground-grass patterns, the 1 case was misclassified as the honeycomb, and 3 cases as reticular. In the honeycomb patterns, 2 cases were misclassified as honeycomb, and 1 case as reticular. Also, in the reticular patterns, 3 cases were misclassified as ground-grass, and 2 cases as

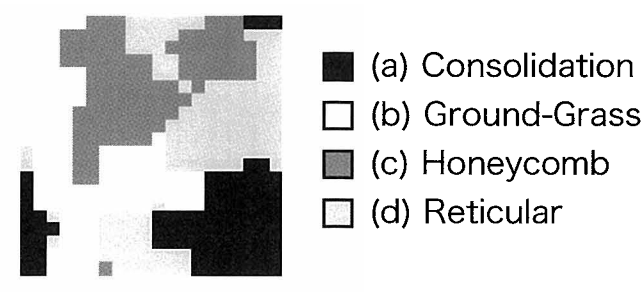

Figure 3: Classification map by SOM and k-means, method. Each color from (a) to (d) represents "Consolidation", "Ground-Grass", "Honeycomb", and "Reticular" image respectively.

Table 1: Classification ability

	Classification result				
	Consolidation	Ground-Grass	Honeycomb	Reticular	Correct
Consolidation	19	0	0	1	95%
Ground-Grass	0	16	1	3	80%
Honeycomb	0	2	17	1	85%
Reticular	0	3	2	15	75%

honeycomb. In this result, the consolidation patterns are the easiest to classify, and honeycomb patterns are the second. The result is reasonable by considering the map arrangement, that is, those two clusters are the furthest location so that these two clusters are easy to distinguish.

5 Conclusion

In this study, the classification accuracy was not so good, but a diagnosis doctor in our group suggests that the relationship among data expressed on SOM looked reasonable, since the Honey-Comb cluster and the Consolidattion cluster in figure 3 are assigned as the furthest clusters.

We consider the map would be useful in assisting radiologists for the diagnosis, because the doctor can grasp the locations between the disease to diagnose and other similar cases.

In the future works, we would investigate other feature for the SOM input. In this study, we only select pixels of ROI with moving average and those of power spectrum. However, in general, the raw image has not translation and rotation invariant, so that we should introduce several features which satisfy these characteristics.

In this study, moreover, we adopt the k-means method which is the most simple clustering method, however, the classification accuracy would be sensitive to the labeling method. Hence, to improve the result accuracy, we should consider the clustering method such that using perceptrons, support vector machines, and so on.

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