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Classification of Idiopathic Interstitial Pneumonia on High-resolution CT Images using Counter-propagation Network

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In order to classify the idiopathic interstitial pneumonias(IIPs), extraction and interpretation of features on high-resolution computed tomography (HRCT) image is considered to be effective. The purpose of our study is to develop a diagnosis support system to help diagnostician of classification for those HRCT images using an artificial neural network called counter propagation network. The CPN is a hybrid type neural network model composed from self-organizing map (SOM) for feature extraction and from multi-layered perceptron (MLP) for classification. Applying the CPN for the IIPs images, we could obtain both a kind of similarity map and classification system.

1. Introduction

In the field of medical diagnosis using image such like computed tomography (CT), the ability of diagnostician has an influence of the quality of diagnosis, so that improving the quality of diagnosis with objectivity is difficult task. The second opinion system, which means plural diagnosticians opinions are considered for diagnosis, is an answer for the problem. while the burden of diagnosticians may become large. Especially, since the variation of image patterns of diffuse lung disease which is treated in this paper is large, it takes a lot of cost to become a skilled diagnostician. Thus, the diagnosis aid system using computer is desired for objective diagnosis in these decades. The computer aimed diagnosis (CAD) system is designed to provide a second opinion using computer analysis from the obtained images, and we can consider many types of CAD systems. In this study, we try to construct a computer diagnosis aid using counter propagation network(CPN), which is a kind of artificial neural network composed of Kohonen's self-organization map (SOM) and multi layered perceptron (MLP)[1]. Fig.1 shows the schematic diagram of the CPN concept. The Kohonen layer corresponds to the SOM part and, Grossberg layer corresponds to the MLP part.

The SOM is a kind of unsupervised learning model which provide a clustering algorithm for input data[2][3].

The MLP is one of the most popular neural network model using supervised learning such like back propagation, and it can classify input patterns without explicit rules. In the CPN, Roughly speaking, the SOM part conduct as a feature extractor, and the perceptron part conduct as a classifier. In the SOM part, several relationship among high-dimensional input data, such that images, sounds and so on, are usually embedded into a 2-dimensional lattice structure called "map". In each lattice point on the map, information representation unit is assigned. Conventionally, naive similarity measure units are used, however, we use more complex information representation unit that include neural network module for representation. This type of SOM is called modular-network SOM (MNSOM)[4].

In the embedding process called learning of the SOM, similarities between inputs data are used, and similar data are inclined to assign in near place in the map.

The merit of using SOM for the CAD system is on the ability of visualization of similarity relationship on the map . For interpretation of the result obtained from the SOM, we introduce a classification layer into the previous work[5], and the network architecture becomes a kind of CPN as the result.

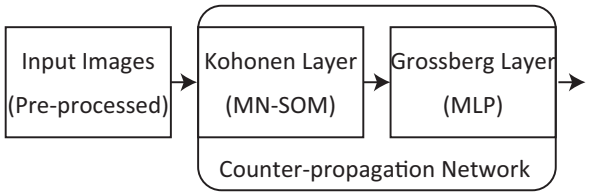

Fig. 1 The schematic diagram of the Counter-propagation network. Input image is processed by the Kohonen layer with SOM type network, at first. Then, the output of the SOM is classified by the MLP corresponding to the Grossberg layer.

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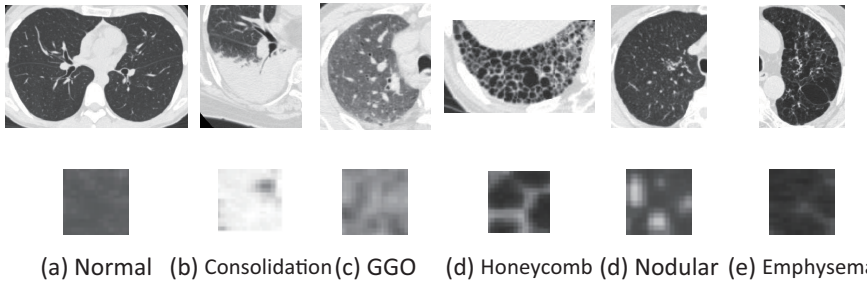

Fig. 2 Typical CT images of diffuse lung diseases: The top row shows each overview, and bottom shows magnified part (ROI) of each lesion. From (a) to (e) represents "Normal", "Consolidation", "GGO", "Honeycomb", "Nodular" and "Emphysema" image respectively.

In the end of the CPN learning, which are both SOM and MLP learning, similar input images are represented in the neighbor lattice points. As the result, we can easy to grasp the relationship between input data by seeing the map. that describe the similarities among high-dimensional input data. Hence, we consider the map as a good decision making support tool for objective diagnosis.

In this study, We developed a prototype CAD system for classifying diffuse lung disease, which called idiopathic interstitial pneumonia (IIP). Our CAD system take a segmented image which is taken by the high resolution CT (HRCT) of patients of lungs, and classify the input image into following named classes, that is, consolidation, ground-grass opacity (GGO), honeycomb, emphysema, nodular, and normal classes. The lesion of this disease is spread in lung, and have a lot of image patterns even in the same class. Fig.2 shows a typical example of each CT image. The top row shows a axial overview of HRCT image, and bottom row shows magnifications of each lesion.

2. Method

In this section, we explain the component of the CPN architecture, that is, one is SOM (MN-SOM) model which is conducted as a feature extractor, and the other is MLP which is conducted as a classifier. Thus we explain them respectively.

2.1 Feature extraction part

In order to extract feature and to visualize the similarities of input data, we applied the MN-SOM. In the field of neural network model, the word SOM is regarded as network architecture and unsupervised learning model. From the viewpoint of the network architecture of the SOM, it consists of neuron like units assigned in a 2 or 3 dimensional lattice, and each datum is represented at a point in the map.

Hence, it is useful when each input datum is ordered by similarities against other data, that is, similar data are arranged near points in the map. As the result, we can visualize the relationships of the high-dimensional input data on the 2-dimensional map in the meaning of similarity. To realize this ordering feature, winner take all (WTA) and neighborhood learning mechanism are adopted usually.

Moreover, we introduce MN-SOM architecture to increase representation ability for the input data. In the conventional SOM, each lattice have a single unit which have a preferred feature called reference vector. In contrast, MN-SOM assigned MLP for each lattice shown in the fig.3.

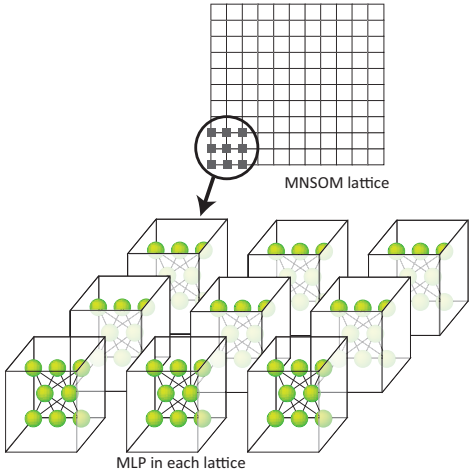

Fig. 3 Schematic diagram of MNSOM[4]: The map consists from square lattice, and each vertex have network architecture.

2.1.1 MN-SOM learning algorithm

The learning algorithm for MN-SOM is a naturally extension of the conventional SOM, that is, we choose a winner MLP in the lattice for an input at first, and then we modify the neighborhood of the winner. We represent each lattice point as $\{n_i\}$ where i means the location index in the map, and the number of nodes as N.

We assume a training input vector set $\{\boldsymbol{x}_p^c\}_{p=1\cdots P_c}$ where p represents the pattern index, and c represents category index to classify. In this study, the dimension of these vectors $\boldsymbol{x}_p^c$ are M that represents the number of input image pixels. Also, we can represents the class label vector as $\boldsymbol{t}_p^c$, which has C dimensions that means the number of categories to classify, for each input vector $\boldsymbol{x}_p^c$. In the class label vector $\boldsymbol{t}_p^c$, the only c-th element, which corresponds to the class the training image $\boldsymbol{x}_p^c$ belongs to, has 1 and other elements have 0.

Now, we can represent the output mappings of the MLPs for $\boldsymbol{x}_p^c$ as $\{\boldsymbol{m}_i(\boldsymbol{x}_p^c;\boldsymbol{w}_i)\}_{i=1\cdots N}$, where $\boldsymbol{w}_i$ represents the weight of the MLP on lattice n_i. Each MLP has M input units which is same as the input vector dimension $\boldsymbol{x}_p^c$, and output layer has C units which is same as the number of categories to classify.

In the learning of the MN-SOM, at first, we choose a winner for the input pattern $\boldsymbol{x}^p$ When we represent the winner node as n_{i^*}, the output of the MLP assigned to the winner node for the training input $\boldsymbol{x}^p$ should have minimum distance to the class label vector $\boldsymbol{t}^p$. Thus we calculate every lattice MLPs distance for each class

$$E_i^c = \frac{1}{P_c}\sum_{p=1}^{P_c}\|\boldsymbol{t}_p^c - \boldsymbol{m}_i(\boldsymbol{x}_p^c;\boldsymbol{w}_i)\|^2. \tag{1}$$

Then we can choose a winner node n_{i^*} for each class c

$$i_c^* = \mathrm{argmin}_i E_i^c. \tag{2}$$

Then we carry out neighborhood learning as follows. We calculate neighborhood function as following Gaussian type function,

$$\varphi_t^c(n_i) = \frac{1}{Z_t}\exp(-(D(n_i, n_{i_c^*})/\sigma_t)^2), \tag{3}$$

$$Z_t = \sum_{c'=1}^{C}\exp(-(D(n_i, n_{i_{c'}^*})/\sigma_t)^2), \tag{4}$$

where $D(n_i, n_j)$ means the Euclidean distance between lattice points n_i and n_j. σ_t controls the spreading of the neighborhood function which corresponds to the number of training epoch t, and the value usually reduce in proportion to the training epoch increasing. Then, we can update the n_ith MLP's weight by the error back propagation (BP) method corresponding to the weighted error[6)7)8)]:

$$\Delta\boldsymbol{w}_i^t = -\eta\sum_c \varphi_t^c(n_i)\frac{\partial E_i^c}{\partial \boldsymbol{w}_i} \tag{5}$$

$$\boldsymbol{w}_i^{t+1} = \boldsymbol{w}_i^t + \Delta\boldsymbol{w}_i^t. \tag{6}$$

In the MN-SOM learning, these WTA processes and neighborhood trainings are carried out until the map is converged.

2.2 Classification layer

When novel input is given and mapped into the the MN-SOM layer, we can grasp the position of the input in the map. To categorize the input, several classifier is required, and we construct this classifier by MLP at the Grossberg layer in fig.1. The input of for this classifying MLP is the response of the MN-SOM. In the previous section, we define the number of lattice points are N, and each MN-SOM node has C output units, so that we can assume the number of the input for classifying MLP as NC units. Also we assume the number of the classifying MLP as C that is the number of categories.

When an the input image for classifying are given, we calculate the MN-SOM response at first. Each position n_i responds the C dimension vector $\boldsymbol{m}_i$ by each trained MLP in MN-SOM layer. Then, these vectors are input to the classifying MLP for classification.

To obtain this classifying function, we adopt the BP for the training of the classifying MLP. Assuming the output of the clarifying MLP for input pattern $\boldsymbol{x}_p^c$ as $y(\boldsymbol{x}_p^c;\tilde{\boldsymbol{w}})$ where $\tilde{\boldsymbol{w}}$ represents the weight parameter in the MLP, we can consider the cost function as

$$E(\tilde{\boldsymbol{w}}) = \sum_c^C\sum_p^{P_c}\|\boldsymbol{t}_p^c - y(\boldsymbol{x}_p^c;\tilde{\boldsymbol{w}})\|^2, \tag{7}$$

and the update rule of the MLP is

$$\tilde{\boldsymbol{w}}^{t+1} = \tilde{\boldsymbol{w}}^t + \Delta\tilde{\boldsymbol{w}}^t \tag{8}$$

$$\Delta\tilde{\boldsymbol{w}}^t = -\eta\frac{\partial E(\tilde{\boldsymbol{w}}^t)}{\partial\tilde{\boldsymbol{w}}}. \tag{9}$$

3. Experiment

In this study, we evaluated the system with 3087 images (Consolidation:124, GGO:589, Honeycomb:526, Emphysema:737, Nodular:360, and Normal:751). Normal class represents the image from healthy donor. On the consolidation image, we cannot recognize the vessels since lesion have too much high CT values such like water. GGO appears the light distributed lesion, and we can recognize vessels in contrast. Emphysema represents distributed low CT values area. Nodular represents small ($<$ 5mm) nodule patterns.

The acquisition parameters of those HRCT images are as follows: each slice image consists of 512 x 512 pixels, and pixel size corresponds to 0.352 mm, slice thickness are 2 mm. The origin of these image data is provided Yamaguchi University Hospital.

3.1 Pre-processing for Input

In usual, the HRCT image consists of 512×512 pixels. However, the whole image includes not only interest anatomy lung, but also another anatomies. Hence, in our system, we assume an input image is a part of HRCT image called "region of interest (ROI)" , which is segmented by a diagnostician. The size of ROI is configured as $32 \times 32 = 1024$ pixels. To reduce the calculation cost, we transform the ROI image pixel values into the histogram as following. In order to emphasize the lung disease, we apply the following ramp filter for the ROI image pixels represented by $\boldsymbol{I}$:

$$h_j = \begin{cases} 0 & (I_j < I_{\min}) \\ \frac{\Delta h}{\Delta I}(I_j - I_{\min}) & (I_{\min} < I_j < I_{\max}) \\ h_{\max} & (I_j > I_{textmax}) \end{cases}, \tag{10}$$

$$\Delta I = I_{\max} - I_{\min}, \tag{11}$$

$$\Delta h = h_{\max} - 0. \tag{12}$$

h_j means the filtered value for the j-th pixel value I_j in the ROI. $I_{\min}$ and $I_{\max}$ are upper and lower saturation bound respectively, and $h_{\max}$ means the upper mapping value for the $I_{\max}$. In this study, we set the $I_{\min} = -1070$, $I_{\max} = 150$, and $x_{\max} = 31$ respectively. Average histogram for each class is shown in fig.2.

Moreover, in order to obtain tolerance for the image shifting and rotation, we introduce

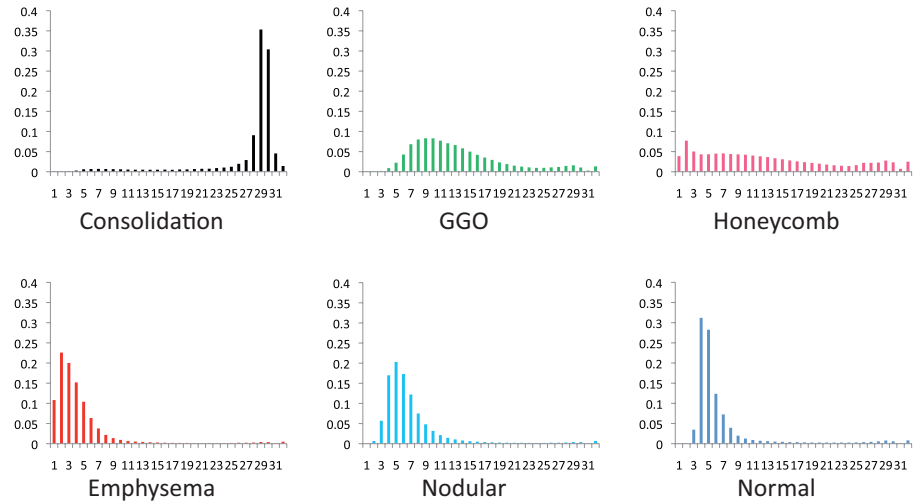

Fig. 4 Mean histogram of the input vector for each class c.. The top row shows the mean histograms of Consolidation, GGO, and Honeycomb classes, and the bottom shows of Emphysema, Nodular, and Normal classes..

a gray level histogram of the pixel values for input vectors $\{\boldsymbol{x}_p^c\}$. When we set bin size of histogram as 1, we can obtain a 32 gray levels histogram for the filtered image $\{h_j\}$. We adopt the histogram as the input for the CPN, so that, the input dimension of the vector $\{\boldsymbol{x}_c^p\}$ are 32 and frequency of the pixel values in ROIs will be input the CPN. Fig. 4 shows the mean histogram of each class. We can see the Normal, Emphysema, and Nodular classes have much more low pixel values, in contrast to the Consolidation class, and Honeycomb class have distributed pixel values.

3.2 Evaluation method

In order to evaluate the ability of our CAD system, we apply cross-validation method[9)8)]. Applying this method, we divide input patterns $\{\boldsymbol{x}_p^c\}$ for 3 groups, and use them as following, that is, one is for evaluation and others are for system construction alternately.

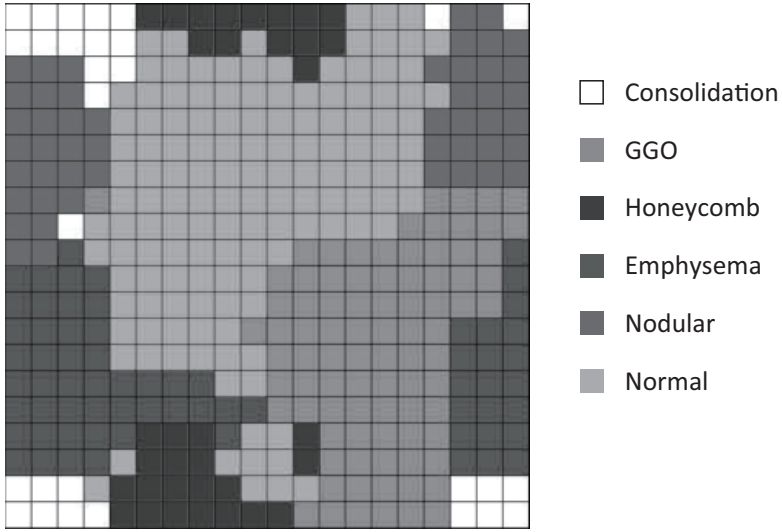

Fig. 5 Result of classification map of MNSOM. The squares in the map shows the lattice points, and each color corresponds to the class.

3.3 Training Configuration for the CPN

We construct CPN for each training set in the cross-validation method as following. At first we train the MNSOM in the Kohonen layer. We set the size of MNSOM as 20×20 lattices, and we assume that the map has the periodic boundary. Each weight of MLP at lattice n_i, which is $\boldsymbol{w}_i$ in eq.(6), are initialized by small random variables $[0.0001, 0.0005]$. and update each MLP assigned on the vertex by the update rule eq.(6). Assuming 1 epoch as the every input vectors in the training set are given to the MNSOM, we consume 4000 epochs for the MNSOM training. In the MNSOM training, the training coefficients are varied by the epoch number t: $\eta = \eta_0(1 - \frac{t}{T})$ where $\eta_0 = 0.2$, and $T = 4000$.

After finishing of the training on the MNSOM, we train MLP in the Grossberg layer. The MLP is updated by the eq.(9), and the weights $\tilde{\boldsymbol{w}}$ are also initialized by small random variables $[0.0001, 0.0005]$.

Table 1 Classification ability by CPN: Total correct ratio is 77.6%

	Classification result with CPN						
	Cons.	GGO	Honey.	Emphy.	Nodul.	Norm.	ratio
Consolidation	**49**	25	1	4	26	20	39.5%
GGO	8	**505**	5	15	31	25	85.7%
Honeycomb	8	49	**406**	28	0	35	77.2%
Emphysema	4	2	4	**663**	44	20	90.0%
Nodule	2	73	2	45	**137**	101	38.0%
Normal	0	47	19	30	15	**640**	85.2%

Table 2 Classification ability by K-means method[5]: Total correct ratio is 42.6%

	Classification result with K-means						
	Cons.	GGO	Honey.	Emphy.	Nodul.	Norm.	ratio
Consolidation	**119**	3	2	0	0	0	96.0%
GGO	23	**210**	67	0	202	87	35.7%
Honeycomb	20	134	**103**	12	166	91	19.6%
Emphysema	0	6	22	**569**	25	115	77.2%
Nodule	0	4	14	105	**28**	209	7.8%
Normal	0	13	37	339	77	**285**	38.0%

4. Results

Fig.5 shows the result of the MNSOM in the CPN. Each class in the map indicate cluster like occupation. When the input image will be mapped into the center of the cluster, we can grasp the input as a typical disease example. On the contrary, the map is near the bound of several classes, we can infer and take care for the possibility of several diseases. Emphysema, nodules, and normal classes are assigned near position in the map each other, that is, the boundary length of each classes are longer than the other boundaries.. We consider this property come from the similarity of the input patterns shown in fig.4. 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 of cross-validation method, the number of patterns in

the training set is 2058, and that of the evaluation set is 1029. The average classification rate 77.8 % is obtained. Table1 shows the detail classification result. Each row shows the input class, and each column shows the classification class. Thus diagonal line shown in bold numbers represents the number of correct classifications. For example, in the consolidation patterns, 25 cases are classified as GGO, 1 case is honeycomb, 4 cases are emphysema, 26 cases are nodular, and 20 cases are normal class. From the table1, consolidation and nodular classes are hard to classify. The images of nodular class includes several small nodule patterns, and this pattern looks similar to the vessels in the normal class. We estimate that the consolidation class is one of the easiest to classify, however, the result is negative. We consider this reason come from the small number of consolidation patterns in the input set, that is, the MLP in the Grossberg layer are overtraining with other classes, and the consolidation class fall into underestimation as the result.

Table2 shows the result evaluation by our previous model[5]. Our previous model evaluate the classification by K-means method, that is, MLP in the Grossberg layer was substituted by the K-means method. In the result of table2, only the consolidation result is superior to our model. Especially, GGO and honeycomb class input have possibility to be classified as every class except consolidation. Thus, we consider the MLP in the Grossberg layer is meaningful for the classification.

5. Conclusion

In this study, the classification rate is not so much good, but the relationship among data class expressed on MNSOM looked very reasonable. We consider the map would be useful in assisting diagnosticians for the diagnosis, because these doctors can grasp the locations between the disease to diagnose and other similar cases.

In the future works, we should investigate other feature for the MNSOM input. In this study, we only apply the histogram of pixels in ROI. We can consider other features such like statistical values of the moment of histograms, texture analysis feature ans so on.

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