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Convolutional Self Organizing Map

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***Abstract*—Recently, deep learning became very popular, and was applied to many fields. The convolutional neural networks are often used for representing the layers for deep learning. In this paper, we propose Convolutional Self Organizing Map, which can be applicable to deep learning. Conventional Self Organizing Map uses single layered architecture, and can visualizes and classifies the input data on 2 dimensional map. SOMs which uses multiple layers are already proposed. In this paper, we propose Self Organizing Map algorithms which include convolutional layers. 2 types of convolution methods, which are based on conventional method and inspired from Self Organizing Map algorithm are proposed, and the performance of both method is examined in the experiments of clustering image data.**

I. Introduction

Deep learning[1] becomes very popular in the world, and many applications using Deep Learning are already developed. For example, it is applied to image processing, natural language analysis, big data analysis, internet search and so on. Recently, the alpha go developed by Google defeats the professional top go player in spite of the other software which uses classical method is still in top amateur level in the world competition which is held after the play of alpha go.

Almost Deep learning methods use deeply layered neural network. Deep learning methods are classified roughly into two classes, Deep Belief Network(DBN)[2] and convolutional neural network(CNN)[3]. DBN is the simple layered network which uses probabilistic neurons as hidden unit. CNN is the layered network which includes convolution layer between the neural network layers. In the convolution layer, the output of neural network is processed by max pooling operation. As the neural network, conventional multi-layer perceptron which uses back propagation for learning is used often. For both method, the network is initialized by using the stastical method or light weight learning method to train the deeply layered network effectively. As mentioned before,these methods are almost well established, and applied to commercial application. For further progress, the application of other architecture of neural network is required.

In this paper, we propose CNN which uses Self Organizing Map (SOM)[4] as neural network. Self Organizing Map is the neural network which uses single layered network architecture. The learning method is classified to feedforward type and unsupervised learning. Self Organizing Map is mainly used for clustering of unknown data, and visualization of the relationship among the data and change of the data by time. As the layered Self Organizing Map, SOM-2 or SOM-n is proposed in by T.Furukawa[5]. SOM-2 and SOM-n is simply layered SOM which does not include other type of layers. In this paper, we propose the Convolutional SOM (CSOM) which includes convolutional layers between the SOM layers. And, 2 types of convolution method, which are the implementation of conventional method to CSOM, and the convolution method based on SOM, are proposed. These methods use SOM for neural network, and novel convolution methods which based on the feature of SOM. It may be able to extract the other features of learning data compared with conventional methods.

In this paper, the algorithm of CSOM is explained in section 3, and the experimental results using image data are mentioned in section 4.

II. Convolutional Neural Networks

Deep learning is a new class of machine learning method. And most of the deep learning algorithms are based on artificial neural networks using deep layered structures. However, the simple learning algorithm which were successful for training shallow layered structures failed to train deep layered structure. For this problem, some improvements were introduced to initialization of the weight values and to learning algorithms, and showed the successful results. Convolutional neural network(CNN) is also applied to deep learning. CNN is composed of the convolution layer, and max-pooling layer. In the first layer, the input data are processed by kernels. The kernels are trained by back propagation algorithm as to extract the features of the input data which can reconstruct the original data. When the input data is 2D image data, the kernels are applied as the sliding window, and 2-dimensional feature map is generated for each kernel. The 2nd layer integrates the feature map for each kernel to a map with taking the maximum values from the values on the same position on the feature maps The 3rd layer is max-pooling layer which calculates the maximum values in the sliding window. The output of the 3rd layer for each image becomes the extracted feature, and is given to the next CNN for further deep learning. The deep learning using CNN were applied to image classification, and showed good performance. Recently, deep learning methods became almost-well-established methods, and are applied to many commercial applications. As the business, the hardwares, which can implement conventional deep learning algorithms are under development. For theoretical progress, applications of the another architecture of the neural net, and as for CNN, another convolutional methods are required.

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III. Convolutional SOM

In this paper, we implement the structure of CNN using the learning algorithm of SOM. We propose 2 types of convolutional SOM which uses the different types of convolution method.

A. 1st type of Convolutional SOM

1st type of convolutional SOM is a convolutional network which uses the learning algorithm of SOM for learning and convolution method of conventional convolutional NN. Fig.1 shows the structure of 1st type of convolutional SOM. The first

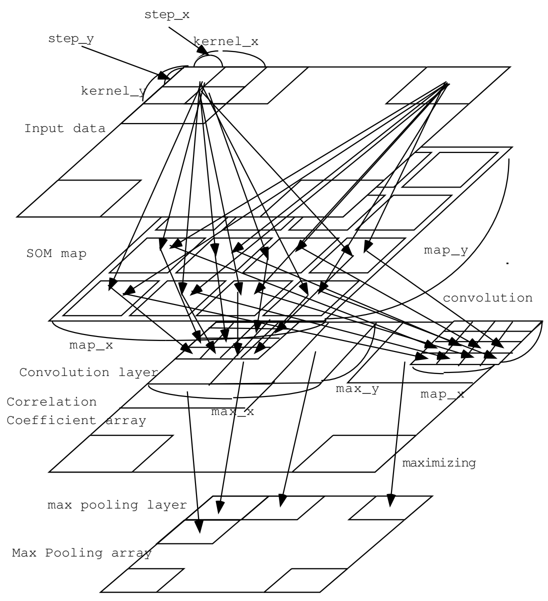

Fig. 1. 1st type convolutional SOM

layer is processed by kernel. The feature map is calculated as the correlation coefficients between input data in the sliding window and kernel. The kernels are trained by SOM algorithm on 2 dimensional map using the input data in the sliding window as input vectors, thus the kernels are arranged on the map based on the similarities among them. The 2nd layer and 3rd layer are almost same as those of CNN,. The output of 3rd layer for each images are given to the next stage of convolutional SOM for deep learning, and also given to the presentation SOM which visualize the relations between the input data.

The algorithm of 1st type is as follows.

1) Learning of kernel map using SOM
   - Initialization of the map
     Initialize the kernels, which are the 2 dimensional array of $kernel_x \times kernel_y$, arranged on the map(Fig. 2) using random values.
   - Learning the kernels
     For each learning data of 2 dimensional array, learn the partial array of $kernel_x \times kernel_y$ with moving the window in every $step_x$ and $step_y$ using batch SOM algorithm(Fig.2).
2) Calculation of the correlation coefficients
   For each partial array of $kennel_x \times kernel_y$ for each learning data, calculate the correlation coefficients against the kernels learned on the map with moving the window in every $step_x$ and $step_y$, and store them to correlation coefficient array(CC) of each input data (Fig. 1).
3) Max pooling of correlation coefficient array
   For each array of $max_x \times max_y$ in correlation coefficient array, calculate the maximum value in the array, and store in max pooling array(MP) of each input data (Fig.1). MPs are used as the input data of next layer.
4) Visualization
   Visualize the relations among MPs using SOM algorithm as the visualization of input data.

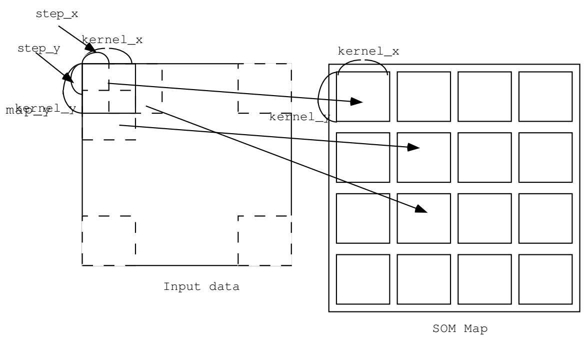

Fig. 2. SOM layer of CSOM

B. 2nd type of convolutional SOM

2nd type of convolutional SOM is the SOM which uses SOM for max pooling operation. Fig.3 shows the architecture of 2nd type of convolutional SOM.

The architecture is identical to the previous one until the convolution layer. After the convolution, all set of the correlation coefficients against the kernels learned on the map are given to SOM(Fig.4) . After learning SOM, the position and euclidian distance of the winner for each set of correlation coefficients are stored in winner array, and the positions of the least euclidian distance in the partial array of $max_x \times max_y$ are stored to minimum pooling array. The algorithm of 2nd type is as follows.

1) Learning of kernel map using SOM

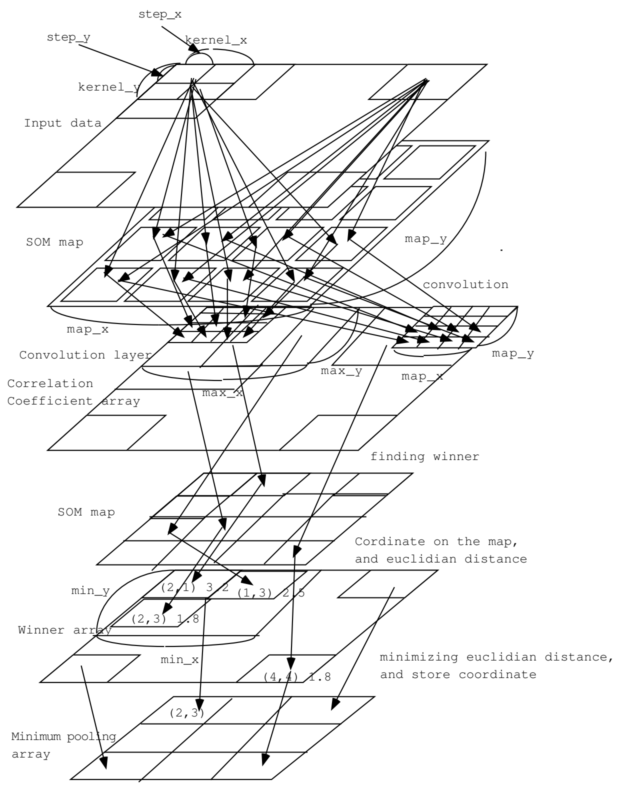

Fig. 3. 2nd type of convolutional SOM

2) Calculation of the correlation coefficients

3) Learning the correlation coefficient arrays on SOM
ALL correlation coefficient arrays against the kernels on SOM map are given to SOM as input data, and learned on the map (Fig.3).
4) Mapping the correlation coefficient array
For each correlation coefficient array, find the winner on SOM map, and store the position in the SOM map and euclidian distance to the winner to winner array(Fig.3).
5) Pooling the position of minimum euclidian distance
For each partial array of $max_x \times max_y$ in winner array, find the minimum euclidian distance, and store the position of winner to minimum pooling array(Fig.3).
6) Visualization

The 1st type uses the maximum values of correlation coefficient array as the translated feature vector of input data. On the other hand, 2nd type extract the feature of correlation coefficient array using SOM, and remap the correlation coefficient array on the map. As for max pooling operation, 2nd type uses the euclidian distance between the correlation coefficient array and winner unit, and with minimizing the euclidian distance conversely to select more significant features.

IV. Experimental Result

In this section, the experimental results are shown. At first, the experiments of visualize the relationship among the images were conducted. 100 images of various type, animal, flowers, scenes and etc. were used as input data. The outputs were shown on the map which learned output of pooling layer. The parameter of the first layer of SOM which learns kernels are set as follows.

- $imagesize = 256 \times 256$
- $kernel_x = kernel_y = 8$
- $map_x = map_y = 8$
- $step_x = step_y 4$

The kernels which are learned by SOM are shown in Fig.4.

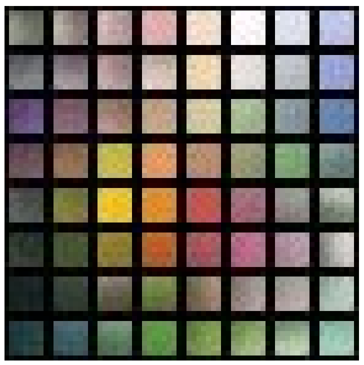

Fig. 4. kernels organized by SOM

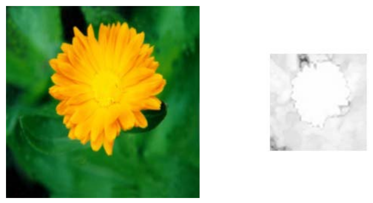

Fig. 5. Translated output of max pooling layer (1st type)

For 1st type convolutional SOM, the parameter of max pooling is set as $max_x = max_y = 16, step_x = step_y = 8$. The output of max pooling layer for the first image (flower) is shown in FIg.5. The output size is 62×62. The visualization of the all outputs of max pooling layer using SOM is shown in Fig.6. The similar type of the images are mapped closely on the map.

For the 2nd type convolutional SOM, the parameter of 2nd layer SOM and minimum pooling are set as $map_x = map_y = 16, max_x = max_y = 16, step_x = step_y = 8$. The output of minimum pooling layer for the first image is shown in Fig.7. The output size is $60 \times 60 \times 2$. The visualizations of the all outputs of minimum pooling layer using SOM with repeating this algorithm are shown in Fig.8. Each layer have 2 layers of SOM, thus the 3rd layer is processed by 6 SOMs.

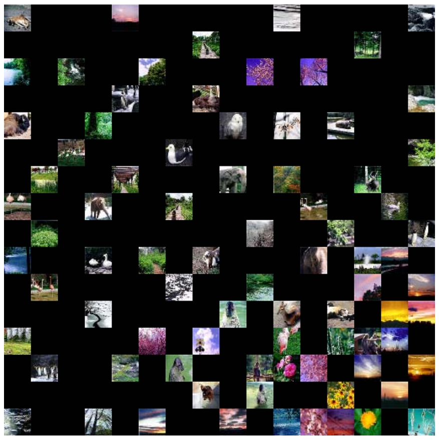

Fig. 6. Mapped images processed by 1st type CSOM

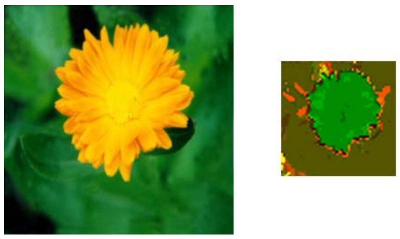

Fig. 7. Translated output of max pooling layer (2nd type)

As same as shown in Fig.6 and Fig8, the similar images are clustered closely on the map, and 2nd type is considered to show better clustering results. However, the difference between 1st and 2nd type of CSOMis not clear. For this purpose, the experiment using mnist handwritting data[6] was conducted. Because SOM is the unsupervised type neural network, the experimental result is evaluated by the rate of successfully clustered data. Table 1 shows the results. 2nd type performs better clustering result in spite of the smaller output size.

TABLE I
EXPERIMENTAL RESULT FOR MNIST DATA

	1st type	2nd type
output size	51 ×51	12 × 12 × 2
Successfully clustered rate	0.873	0.920

V. CONCLUSION

In this paper, we propose 2 types of Convolutional Self Organizing Maps which can be applicable to deep learning as the application of another architecture of neural net to Deep learning and novel convolution methods. !st type is based on the conventional convolutional neural network which translates the input data using max pooling operation. 2nd type uses SOM and euclidian distance between winner neuron and input data for minimum pooling operation instead of max pooling. 2nd type can extract the feature efficiently, and can visualize relations among the input data.

As the feature work, because the proposed method based on the SOM which categorized to unsupervised learning algorithm, the accuracy of classification is worse than those which use supervised learning algorithm.The algorithm which can retrain the network using supervised backward propagation, or supervised type of SOM, which is reported by the author as supervised parato learning SOM, should be applied. And the experiments using other type of input data, for which we are planning to use bioinformatic data and music wave data, should be conducted. And for improvement of visualization, Spherical SOM which can visualize the input data on the sphere can be applied to for output layer.

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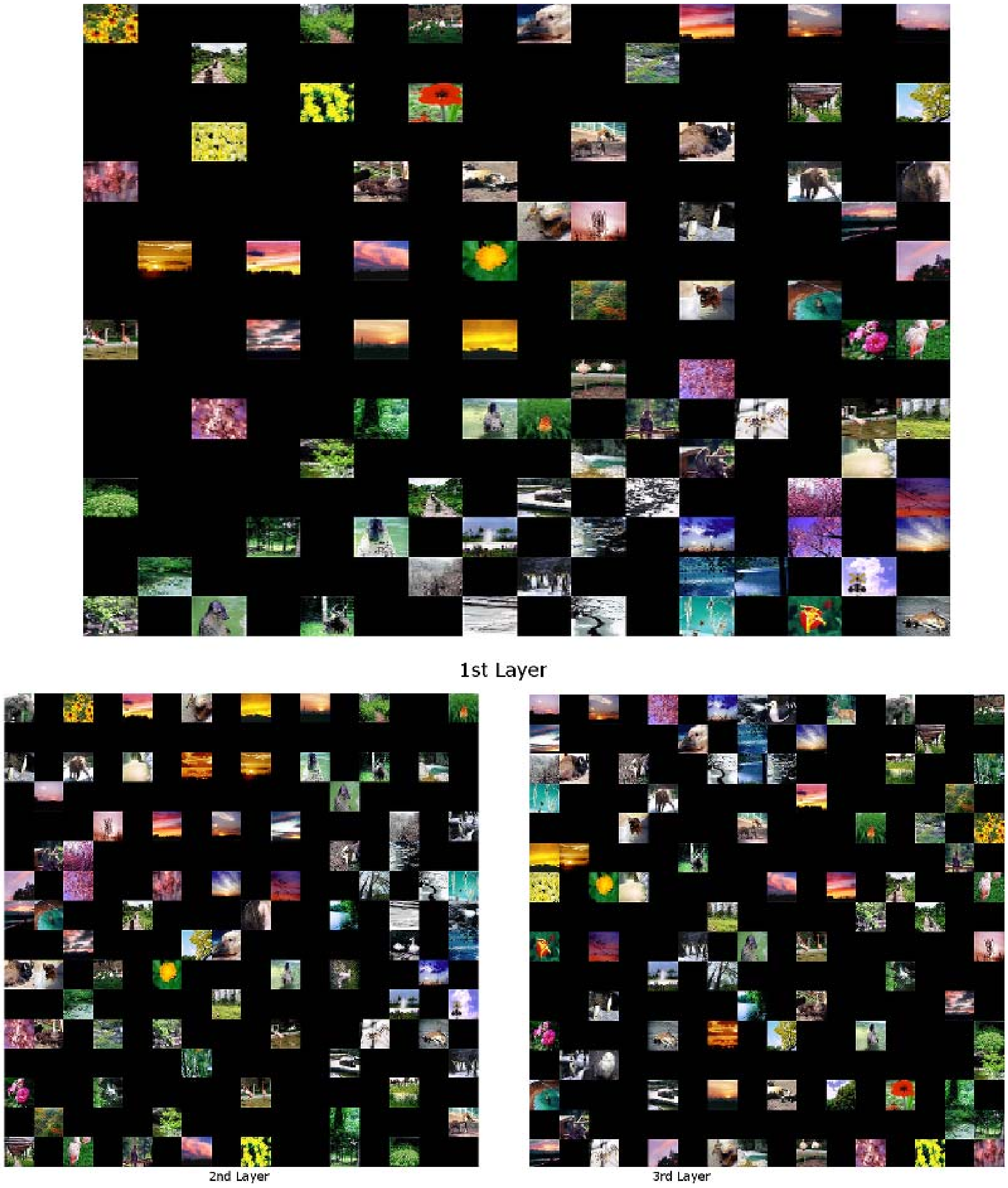

Fig. 8. Mapped images processed by 2nd type CSOM for 1st, 2nd and 3rd output layer