Formal Representation of Images by Pulse Coupled Neural Networks

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Abstract: The contribution analyses the suitable approach for the formal representation of images by Pulse Copled Neural Networks. The formal representation of images is realised by vector of features, that are created by this neural network from multidimensional image space to low dimensional feature space. This approach can radically reduce the dimension of feature space during the feature generation process.

Keywords: feature generation, feature selection, Pulse Coupled Neural Network, formal representation of images.

1 Introduction

Direct image processing in multidimensional image space is very difficult or impossible practically. The image processing would be very complicated and its complexity depends on dimension space of processed images. For that reason image processing is not solved in the input space of processed images with high dimension, in generally. There are available several methods for dimension reduction that cretated new formal representation of images [10].

The goal of dimension reduction is to obtain the significant features for unique image identification. It means, that dimension reduction is transform of an input image space to feature space with radically lower dimension. This transform can dramatically simplify the image processing, indexing, and so on.

The classical methods of dimension reduction are, for example, Karhunen – Loeve transform [18, 19], singular value decomposition (SVD) [12, 30], multidimensional scaling [4], etc.

For the dimension reduction it is possible to use conventional neural networks, for example, Kohonen Self-Organized maps [22-27] or neural networks based on principle component analysis (PCA neural networks) [1, 5, 6, 13, 17, 28]. Thanks nonlinear projection the neural networks can more precisely describe the represented images in the case of lower number of generated features (for example for d ≤ 2). In this case can be achieved the radical reduction of feature dimension space. Advantage of nonlinear projection follows from better mapping of an input multidimensional image space into lower dimensional feature space. Disadvantage of the conventional neural network approach is in high time consuming of learning process mainly by using the gradient type learning methods [3]. Next significant disadvantage of this approach is very high probability to achieve a local minimum of error function during the learning process what cases the end of learning.

The problem is finding the optimal number of nonlinear neurons in the hidden layers. It possible to claim that the conventional (Kohonen or PCA) neural networks are suitable for reduction of input image space with lower dimension by higher number of classified images and higher number of classes.

The topic of our research is focused on Pulse Coupled Neural Networks (PCNN) [14, 15, 16] that radically decrease the high dimension of an image space into very low dimension feature space by feature generation process. This contribution introduces a suitable approach for reduction of feature space by selection of significant features.

2 Pulse Coupled Neural Networks

The Pulse Coupled Neural Network (PCNN) is a biological model based on the mammalian visual cortex, proposed by Eckhorn [7]. The PCNN is advisable to solve tasks as the feature generation for image and pattern recognition [8, 11, 20, 21, 30], image segmentation [32], etc.

2.1 Structure of PCNN

The structure of standard PCNN comes out from structure of input image, which will be processed. It means that PCNN is single layered, two-dimensional, laterally connected neural network of pulse coupled neurons, which are connected with image pixels each other.

Each image pixel is associated with a pulse coupled neuron of specific structure (Fig. 1). PCNN neuron consists of an input part, linking part and a pulse generator. The neuron receives the input signals from feeding and linking inputs. Feeding input is the primary input from the neuron's receptive area. The neuron receptive area consists of the neighboring pixels of corresponding pixel in the input image. Linking input is the secondary input of lateral connections with neighboring neurons. The difference between these inputs is that the feeding connections have a slower characteristic response time constant than the linking connections. The standard PCNN model is described as iteration by the following equations:

$$F_{ij}(n) = S_{ij} + F_{ij}(n-1)\cdot e^{-\alpha_F} + V_F \cdot (M * Y(n-1))_{ij} \quad (1)$$

$$L_{ij}(n) = L_{ij}(n-1)\cdot e^{-\alpha_L} + V_L \cdot (W * Y(n-1))_{ij} \quad (2)$$

$$U_{ij}(n) = F_{ij}(n)\cdot(1+\beta\cdot L_{ij}(n)) \quad (3)$$

$$\Theta_{ij}(n) = \Theta_{ij}(n-1)\cdot e^{-\alpha_\Theta} + V_\Theta \cdot Y_{ij}(n-1) \quad (4)$$

$$Y_{ij}(n) = \begin{cases} 1 & \text{if } U_{ij}(n) > \Theta_{ij}(n) \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

where F_{ij} is the feeding input, L_{ij} is the linking input, n is an iteration step, S_{ij} is an intensity of pixel i,j in the input matrix, W and M are the weight matrices, * is the convolution operator, Y is the output of the neuron, V_L and V_F are potentials, α_L and α_F are decayed constants.

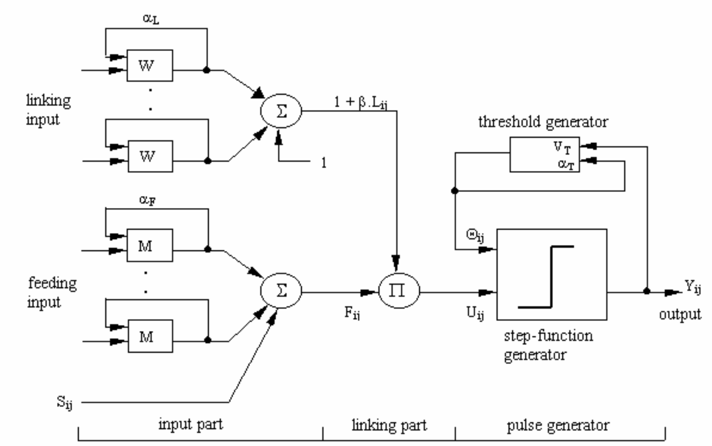

Figure 1
The structure of PCNN neuron

Single signals of the linking input are biased and then multiplied together. Next, input values F_{ij}, L_{ij} are modulated in linking part of neuron. The modulation coupling in relations with more-common additive coupling has one important advantage in feature generation process: a neuron with no primary input cannot be activated. We also obtain internal activity of neuron U_{ij} in the specific iteration step. If internal activity is greater than dynamic threshold Θ then neuron generates output pulse. Otherwise output equals to zero. The neuron output Y_{ij} does not necessarily need to be binary. It is possible to use a sigmoid pulse generator, where the neuron takes the analogue value from 0 to 1.

2.2 Feature Generation by PCNN

The multilevel input image, which is represented by two-dimensional matrix, is through PCNN transformed into a sequence of temporary binary images. Each of these binary images is a matrix with the same dimension as input matrix and it is generated by group of pixels with similar intensity. The sum of all activities in specific iteration step gives one value, which represents one feature for the classification. If we have *N* iteration steps, we obtain *N* features.

The one-dimensional time signal, generated from the feature values of outputs Y_{ij} in every iteration step n is defined as:

$$G(n) = \sum_{ij} Y_{ij}(n) \tag{6}$$

Significant advantage of PCNN is the invariance of generated time signal to rotation, dilatation or translation of images [8, 9, 10, 14, 15, 16, 20, 21]. Therefore PCNN is advisable for the feature generation and pattern recognition in the classification tasks using conventional neural networks or the other methods.

PCNN doesn´t need learning known from conventional neural networks. For new class of images is it necessery to add new etalon of features set only, that represent this class in recognition process.

Several models of PCNN have been developed. The most used PCNN models are, for example, PCNN with modified feeding input [20, 21], fast linking PCNN [20, 21, 14] or feedback PCNN [14]. More details of the PCNN functionality are described in [14, 15, 16].

3 Suitable Aproach to Feature Reduction

Suitable approach to feature reduction is based on the analysis of time signal [9]. The time signal determines, whether an image was rotated, translated or dilated. If two time signals are alike, but translated each other, then comparable images are not identical. If two time signals are alike, but amplitudes are less or bigger, then it is the same image, but dilated. If input images are scale down, then the amplitudes of time signal are smaller. If input images are scale up, then the amplitudes of time signal are greater. The time signals for the same but translated images are identical. The time signals of rotated images are soft deformed in compare with time signal of image in basic position. Due to it is very important to norm the time signal in interval <0, 1>.

The above mentioned approach how to minimise the number of features consist of two steps. The first step is standard feature genaration by PCNN. In this step is the image space *D* transformed to feature space *d* with lower dimension:

$f: R^D \rightarrow R^d, \ d << D$ (6)

The second step is feature selection from generated set of features. The feature selection is characterized by chosen of relevant subset of features s from input set of generated features d, where $s < d$. It means, that it goes to dimenzion reduction of clasiffying space. From description of the time signal and normalization of generated features it is clear, that it is sufficient to identificate the lacalization of relevant features, which can be determine by next approach - feature selection based on looking for the most significant s features. By mentioned approach will be selected s significant features, which are represented by the highest value from generated set of features.

The most important criterion for the feature selection is the minimal classification error. It means, that the feature selection process is connected with used classification method and with type of classified images.

4 Experiments and Results

Experiments described in this paper were realized on various textural and figural images. For demonstration purpose in this paper are shown results of 21 texture images with raster 512 x 512 pixels and bit depth equals to 8 (Fig. 2). Testing set of images was created from rotated images in interval <0°, 200°> with step 30°. The number of iterations for feature generation was 30.

Results of experiments for feature selection, based on looking for the global maximum of the first s features, are shown in Fig. 3, where s axis represents number of selected features and y axis clasification correctnes [%] by Euclidean distance.

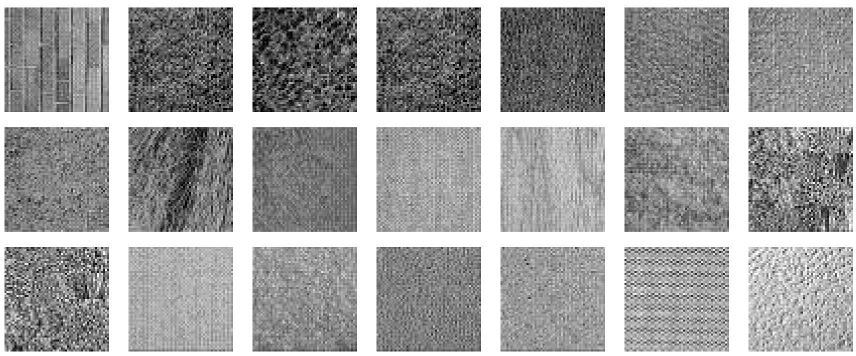

Figure 2
Sample of testing images with raster 512 x 512 pixels

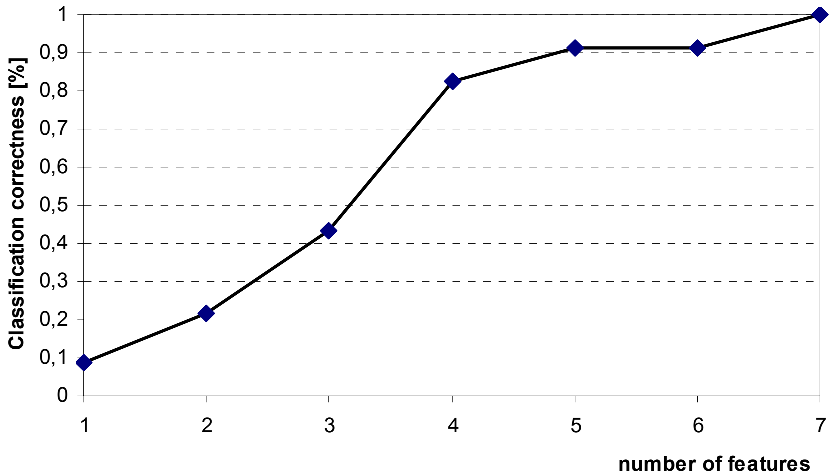

Figure 3
Dependence of classification correctness on number of selected features

From experiments resulted, that PCNN due to shown aproach is able to more precisely describe this set of classified images in the case of small number of selected features for $s = 7$. With enlarging of training set on new classes of images is very probable to have selected more features for good formal representation of images.

Conclusions

The goal of this contribution is introduction of a suitable approach to reducing of features by PCNN. From point of number of classified classes can be mentioned, that PCNN is suitable for reduction of input image space with high dimension and lower number of classified classes.

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