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ULTRASOUND MEDICAL IMAGE PROCESSING USING CELLULAR NEURAL NETWORKS

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Abstract. An application of the Cellular Neural Networks (CNN) to ultrasound medical image processing is considered in the paper. Since the goal of the processing is extraction of details, the corresponding linear and non-linear filters, and their implementation on the CNN are developed. It is shown that the best result is obtained by combination of the different filters. All the processing algorithms may be implemented on the CNN. Simulation results based on the CNN-processing of images corresponding to larynx cancer are also presented.

1. Introduction

CNN introduced in [1] and then intensively developed has become a brilliant mean for solution of the different problems of image processing and recognition. An implementation of the two-dimensional linear and non-linear filtering in spatial domain has to be noted first of all. An application of the CNN to medical image processing is connected with an implementation the different filters for extraction of the small details against complicated image background on the CNN. Some of such filters, their CNN-implementation, and application to mammogram analysis have been developed in [2-4]. The spatial linear filters for high and global frequency correction, and their CNN-implementation have been proposed in [4-5]. These filters are good approximations of the corresponding frequency domain filters. They are able to extract the smallest image details, or details of the medium sizes (in comparison with the sizes of image). The last property has been used not only for mammogram analysis, but for analysis of the x-ray pictures of lungs also. So, the high efficiency of the CNN for medical x-ray image processing has been proven in [2-5].

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It will be very interesting to investigate possibility of the ultrasound image processing using CNN. Our goals are: 1) to remove a noise which is the result of extra signal reflections; 2) to extract the smallest details against image background; 3) to extract the details of a requested size. This paper is devoted exactly to developing of the corresponding algorithms, and their CNN-implementation.

2. Some useful filters, and templates for their CNN-implementation

A quality of the ultrasound image is characterized by frequency and amplitude of the ultrasound signal. A problem of the quality improving of ultrasound images is actual because it is always very important to make the corresponding image more sharpened, free of false reflections. Taking into account this fact we will consider here some filtering algorithms, and their CNN-implementation which always may be used for significant improvement of the ultrasound image quality, and for extraction of the image details.

The first problem of ultrasound image processing is the noise reduction. The problem is that the ultrasound signal usually gives some extra reflections which are visible as noise, and which are the preventing factor for image interpretation. Taking into account that preservation of the image boundaries is very important we have to use a filter which ensures it. It was recommended in [5] to use the rank-order, or the simple low-pass linear filter to remove Gaussian, or uniform noise. Both filters may be implemented using CNN. But recently the multi-valued non-linear filter (MVF) has been proposed [6, 7], and it was shown that it is more effective than rank-order and simple low-pass filters either from the point of view of noise removal, and boundaries preservation. A two-dimensional MVF is defined by following equation:

$$\hat{B}_{lj} = P(w_0 + \sum_{\substack{l-n \le s \le l+n \\ j-m \le t \le j+m}} w_{st} Y_{st}) \qquad (1)$$

where Y_{st} are the signal values from a local window around ij-th pixel (in a complex form obtained by transformation $\varepsilon^{B_{st}} = \exp(i2\pi\, B / k) = Y_{st}$, where B_{st} is the integer signal value, k is the value of k-valued logic, and has to be equal to number of the gray levels, i is an imaginary unit), l,j are the coordinates of the filtered pixel, $n \times m$ is a filter window, w_{st} are the filter's coefficients (complex-valued in general), P is a non-linear function, which is an activation function of multi-valued neuron [6,7]:

$$P(z) = j, \text{ if } 2\pi\,(j+1)/k > \arg(z) \ge 2\pi j/k\,, \qquad (2)$$

where j=0,1,...,k-1 are values of the k-valued logic, $z = w_0 + w_1 x_1 + \ldots + w_n x_n$ is the weighted sum , arg(z) is the argument of the complex number z. It is evident from (1) and (2) that MVF may be implemented on the CNN with multi-valued neurons (CNN-MVN) [8]. A CNN-MVN cell (and also CNN-UBN cell, see below) is characterized by following equation:

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$$Y_{ij}(t+1) = P\,[w_0 + \sum_r w_r^{ij} x_r^{ij}(t)]\,, \tag{3}$$

where Y_{ij} is the neuron's output, W_r^{ij} (one may compare with the **B**-template of an original CNN [1]) is the connection weight corresponding to the m-th input of the ij-th neuron, and X_r^{ij} is the value of the m-th input of the ij-th neuron, *P* is the activation function (2). The following template has been proposed in [6] for implementation of the filter (1) on the CNN-MVN:

$$W_0 = C;\; W = \begin{pmatrix} 1 & 1 & 1 \\ 1 & w_{22} & 1 \\ 1 & 1 & 1 \end{pmatrix}, \tag{4}$$

where C is a constant, W_{22} is a parameter. The recommended values for the parameter W_{22} it is easy to obtain from a heuristic point of view. The image boundaries will be preserved effectively with greater values of W_{22} .It is possible to take $1 \le W_{22} \le 10$ (it is clear that $W_{22} > 10$ degenerates the filter with a 3x3 window). The CNN-MVN with a 3x3 local connections is sufficient for an implementation of the filter (1) with the template (4).

After the noise reduction it is possible to concentrate on the extraction of details. We will use highly effective algorithms of frequency correction and edge detection which it is possible to implement on the CNN. The following spatial-domain filters for global and high frequency correction respectively have been proposed in [4-5]:

$$\hat{B}_{ij} = G_1 B_{ij} + G_2 (B_{ij} - B_m) + G_3 B_m + c \tag{5}$$

$$\hat{B}_{ij} = B_{ij} + G(B_{ij} - B_m) + c, \tag{6}$$

The filter (5) is very useful for the extraction of details with medium sizes, the filter (6) gives a good result for the extraction of the smallest details. Here B_m is the local mean value within the window around the pixel B(i,j); B(i,j) and $\hat{B}(i,j)$ are the signal values in (ij)-th pixel before and after processing respectively, G_1, G_3 are the coefficients which define correction of the low frequency, G_2 and G defines correction of the high frequency, *c* is the constant. The both linear filters (5) and (6) may be implemented on the CTNN by following templates respectively (A=0; I=c, notions are standard for CTNN and DTCNN templates):

$$B = \begin{pmatrix} \frac{G_3 - G_2}{nm} & \cdots & & \cdots & \frac{G_3 - G_2}{nm} \\ \cdot & & & & \cdot \\ \cdot & \cdots & G_1 + G_2 + \frac{G_3 - G_2}{nm} & \cdots & \cdot \\ \cdot & & & & \cdot \\ \frac{G_3 - G_2}{nm} & & \cdots & & \frac{G_3 - G_2}{nm} \end{pmatrix} \tag{7a}$$

$$B = \begin{pmatrix} -\frac{G}{nm} & \cdots & & \cdots & -\frac{G}{nm} \\ \cdot & & & & \cdot \\ \cdot & & 1 + G - \frac{G}{nm} & \cdots & \cdot \\ \cdot & & & & \cdot \\ -\frac{G}{nm} & & & \cdots & -\frac{G}{nm} \end{pmatrix} \tag{7b}$$

where *n x m* are the sizes of the local window of the CNN or filter window. The best values for weighting parameters are [4-5]: $G \in [0, 10]$, $G_1 \in [0,1]$, $G_2 \in [0,10]$, $G_3 \in [0,1]$, $c \in [0,255]$.

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MVF defined by (1) also may be used for solution of the high and global frequency correction problem. It should be noted that MVF is not so sensitive to choosing of the weighting coefficients, and gives more effective results [7] in comparison with the filters (5)-(6). Taking into account (1)-(2) we obtain the following generalization of the filters (5) and (6) respectively:

$$\hat{B}_{ij} = P\left[c + (G_1 + G_2)Y_{ij} + (G_3 - G_2)\sum_{Y_{kl} \in R_{ij}} Y_{kl}\right] \tag{8}$$

$$\hat{B}_{ij} = P\left[c + (1+G)Y_{ij} - G\sum_{Y_{kl} \in R_{ij}} Y_{kl}\right] \tag{9}$$

where R_{ij} is a local window around pixel Y_{ij}; Y_{ij} and $\hat{B}_{ij}$ are the signal values in (i,j)-th pixel before and after processing. Evidently, the filters (8) and (9) may be implemented on the CNN-MVN by following templates respectively ($w_0 = c$):

$$W = \begin{pmatrix} G_3 - G_2 & \dots & \dots & G_3 - G_2 \\ \cdot & & & \cdot \\ \cdot & \dots & G_1 + G_3 \dots & \cdot \\ \cdot & & & \cdot \\ G_3 - G_2 & & \dots & G_3 - G_2 \end{pmatrix} \quad \text{(10a)} \qquad W = \begin{pmatrix} -0.5 & -0.5 & -0.5 \\ -0.5 & G & -0.5 \\ -0.5 & -0.5 & -0.5 \end{pmatrix} \quad \text{(10b)}$$

Recommended values for the parameters are the following: $0 \le G_1, G_3 \le 1$, $5 \le G_2 \le 16$, $6 \le G \le 16$.

Finally, very useful non-linear filter which will be very important for us is the filter which defines an edge detection [5]. This processing algorithm is reduced to the separation of the gray-scale image into eight binary planes, their separate processing by Boolean function

$$Y\begin{bmatrix} x_1 & x_2 & x_3 \\ x_4 & x_5 & x_6 \\ x_7 & x_8 & x_9 \end{bmatrix} = x_5 \& (\overline{x}_1 \vee \overline{x}_2 \vee \overline{x}_3 \vee \overline{x}_4 \vee \overline{x}_6 \vee \overline{x}_7 \vee \overline{x}_8 \vee \overline{x}_9) \tag{11}$$

and then to integration of the resulting binary images into the resulting gray-scale image [5]. Since the function (11) is not threshold it can not be implemented using DTCNN, but it is easy to implement it on the CNN-UBN [5] (UBN is the universal binary neuron [5], on which arbitrary (not only threshold) Boolean function may be implemented). Dynamics of the CNN-UBN cell is described by equation (3), also as dynamics of the CNN-MVN cell. The UBN activation function is the following [5]: $P_B(z) = (-1)^j$, if $2\pi(j+1)/m > \arg(z) \ge 2\pi j/m$, where *arg(z)* is the argument of the complex number *z*, *m* is some positive integer: $2 \le m \le 2^n$, *n* is the number of neuron inputs. Learning algorithm for UBN (which is described in details in [5]) gives the following template for implementation of the function (11) on the CNN-UBN:

$$W = (-6.3 \quad -5.6)\begin{bmatrix} (-0.82,\ 0.32) & (-0.95,\ -016) & (-0.04,\ 0.01) \\ (0.25,\ -1.4) & (-0.32,\ -0.05) & (-0.03\ \ 0.01) \\ (0.0,\ 0.10) & (0.63,\ 0.60) & (-0.02\ \ 0.01) \end{bmatrix};\ m = 4 \tag{12}$$

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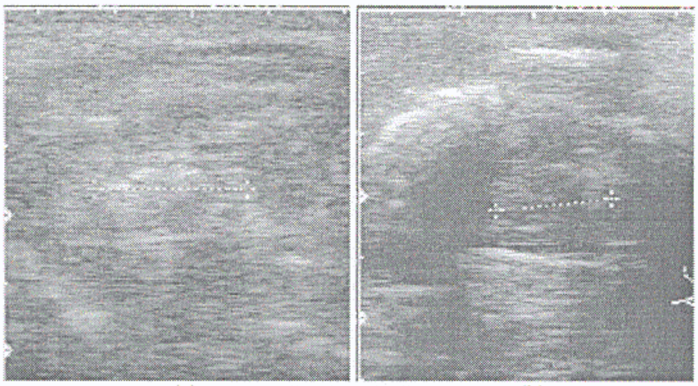
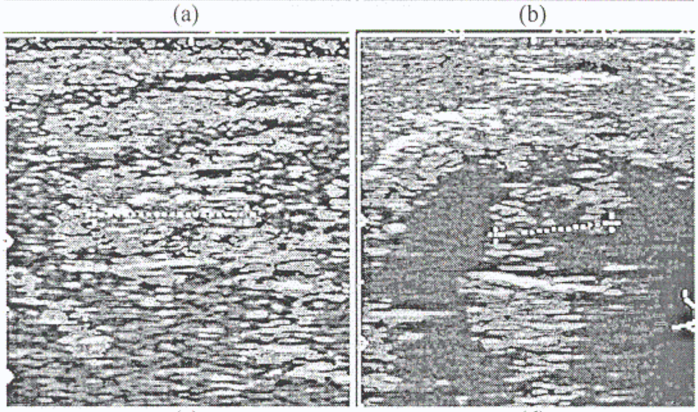
3. Strategy of the processing and simulation results

The strategy of the processing has to lead to the extraction either of the smallest and medium details, and to clear perception of the tissues density. To get such results even in conditions of very low-quality input image we have to recommend the following strategy of the ultrasound medical image processing on the CNN: 1) Reduction of the false signal reflections by template (4) on the CNN-MVN; 2) The high frequency correction by template (7b) on the CTCNN, or by template (10b) on the CNN-MVN to extract the smallest details; 3) The edge detection by template (12) on the CNN-UBN; 4) The combination of the images obtained on the steps 2 and 3; 5) The global frequency correction by template (7a) on the CTCNN, or by template (10a) on the CNN-MVN to extract the details of medium sizes.



(a) (b)



(c) (d)

Fig. 1. CNN-processing of the ultrasound images obtained by investigation of patient with tumor of larynx. (a) - input image before treatment; (b) - input image after treatment (2-weeks ray-therapy). It is very difficult for physician to decide that tumor is destroyed within region under marker, or not. The processing according to the strategy presented here gives the following results: (c) - the resulting image corresponding to input image (a): tumor, its structure and exact sizes are clearly visible; (d) - the resulting image corresponding to input image (b): the significant part of tumor is practically destroyed, which is clearly visible again.

To prove efficiency of the proposed strategy we used software simulator of the CTNN, CNN-MVN, CNN-UBN, and made a couple of experiments with the different ultrasound medical images. The proposed processing strategy has been especially effective for monitoring of the patients with tumor of larynx. An ultrasound investigation of such patients is very difficult (also as x-ray investigation) because of hard difficulties of image interpretation. But CNN-processing solves all the problems. One of the typical examples is illustrated by Fig.1.

4. Conclusions

The main conclusion is a high efficiency of the different CNN types for solution of the problems of image filtering and extraction of details. Such an efficiency is confirmed by ultrasound medical image processing on the CNN.

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