Automatic ROI positioning in ultrasound TCS images using artificial intelligence to Parkinson´s disease risk

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Abstract: - The aim of this work is semi-automatic ROI positioning in transcranial images based on ANN module. We need to learn ANN to accurate positioning of ROI inside substantia nigra of transcranial images. Designed approach is based on image processing and is realized by means of artificial intelligence which has been experimentally simulated in MATLAB software environment. This method is well applicable with Neural Network Toolbox in MATLAB. Within this processing has been worked with a set of TCS images in grayscale and/or binary representation to experimental testing to automatic positioning.

Key-Words: - ultrasound, artificial neural networks,Parkinon´s disease,MATLAB

1 Introduction

Modern medical imaging methods help to diagnose in medicine. This paper is focused on processing of transcranial (TCS) ultrasound images. It is useful to potential Parkinson´s disease diagnosis. We developed a computer program in MATLAB to area measurement of substantia nigra which is described in next part. Described part of application is based on image processing and neural network approach with artificial intelligence elements. The purpose of neural network approach is a positioning of needed ROI in substantia to area computing. All Input files are in DICOM format, see chapter 2.

1.2 Role of SN and Parkinson´s disease

Parkinson's disease (PD) is caused by the death of dopaminergic neurons. It is a degenerative disease of basal ganglias inside the brain, described by James Parkinson in 19th century. The main symptoms of PD include muscle rigidity, tremors and changes in speech and gait, bradykinesia, sleep disorders and more.[1] It is a chronicle disease and initial features sometimes are insignificant for diagnosis.[2]

Substantia nigra (SN; in English "black substance") is a brain structure which is located in the mesencephalon (midbrain) that plays an important role in reward, addiction, and movement, produces important dopamine for correct function of CNS (Central nervous system). SN is very important part of midbrain and is well recognizable by ultrasound. Detailed information about SN and echogenicity in image are available in [1], [2] and [3]. The following figure shows the position of basal ganglias where is located SN.

[1] http://www.mdvu.org/library/disease/pd/

[2] http://www2.parkinson.org/Document.Doc?id=618

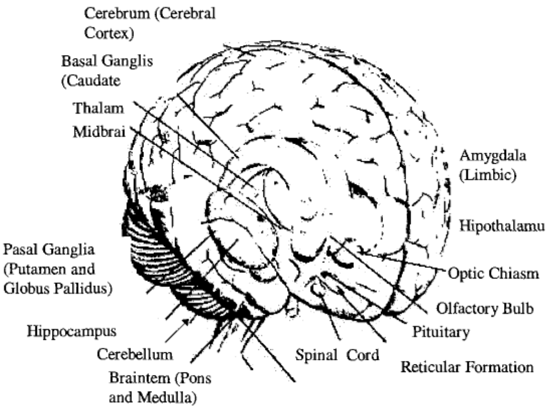

Fig. 1 – Position of basal ganglias where is situated SN

2 Practical experimental processing

In this section we will describe designed algorithm based on ANN; ANN module recognition (Fig.2). The following flow-chart shows how to work our designed method.

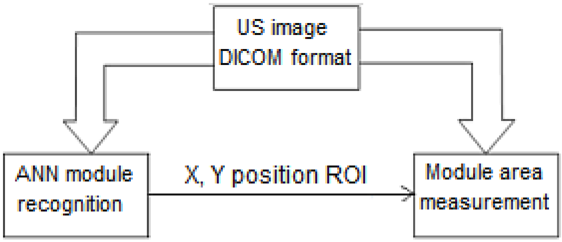

Fig. 2 – Flow-chart of whole processing

In the following parts we will present ANN module recognition in details and shortly we will introduce Module area measurement at the end.

2.1 Input images and their pre-processing

As input files we have a set of TCS ultrasound images in DICOM (*Digital Imaging and Communications in Medicine*)[3] format which is worldwide standard for medical imaging and each image contains metadata about image acquisition, used modality, bit depth and more. MATLAB with Image Processing Toolbox was selected because provides powerful tools for image processing and also supports DICOM files.

Ultrasound B-MODE scanning which is used for this TCS images is generally applicable for soft tissues. For details about diagnostic US benefits, see [16].

The following figure shows the input TCS image with highlighted SN area 50×50 mm loaded into MATLAB Figure.

[3] http://www.rsna.org/Technology/DICOM/index.cfm

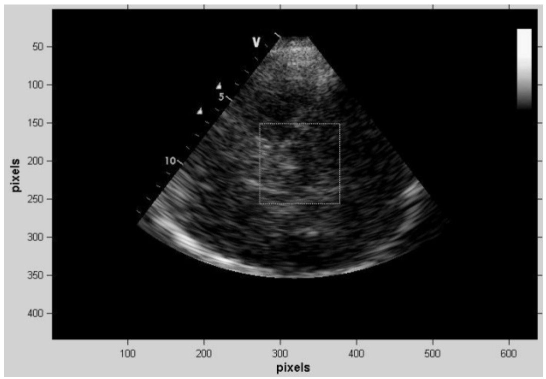

Fig. 3 – Input TCS image with position of ROI window

For the main processing we will use these windows 50×50 mm measured from native US axis.

For whole processing we need all input images in grayscale, which means R=G=B. If input image is in 24-bit depth, rgb2gray function converts this input by means of the following formula into grayscale image:

$$I = 0{,}299 \times R + 0{,}587 \times G + 0{,}114 \times B. \tag{1}$$

Each pixel p_i in image has the intensity value from range $\langle 0;\ 255 \rangle$, it is a real matrix with these matrix elements. It is the main requirement for this processing; classifying PD and non-PD cases. We must find the regions inside SN which can be critical for PD diagnosis.

2.2 Main processing with ANN

The main processing is based on artificial neural network (ANN) approach followed by the area measurement inside ROI SN. Image recognition is well applicable problem for artificial neural network (ANN) using. The idea of ANN is motivated by biological neural networks in brain. Generally speaking, ANN are the interesting trend not only for image processing, ANN are also used for prediction, matching, clustering, etc. The basic element of ANN is artificial neuron also called as processing element (PE). These neurons are connected to network. We will not describe ANN theory; it is available in [7], [10] and [13]. Firstly, we can divide whole processing:

- ANN module
- area measurement

As we mentioned, ANN recognition module will be presented in details.

For this processing we assume that input images were cut to 50x50 mm ROI with SN (Fig. 3), it has

ISBN: 978-1-61804-089-3

been appointed by neurologist, for details see [2] where this operation was presented.

We require the elliptical ROI with area A = 50 mm^2 with rake angle of 60°, which is needed to ROI definition. Shape, size and rake angle of ROI were assigned by erudite neurologist. So, we need the ellipse how shows the following figure.

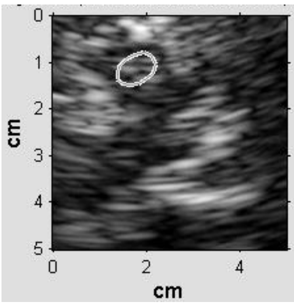

Fig. 4 – An example of applicable elliptical ROI

We will introduce how to locate this ellipse inside SN in appropriate position, see example on Fig. 4. The aim of our problem is to applicably locate this ellipse inside SN with ANN.

2.3 ANN module recognition

The following figure shows the block diagram of ANN processing.

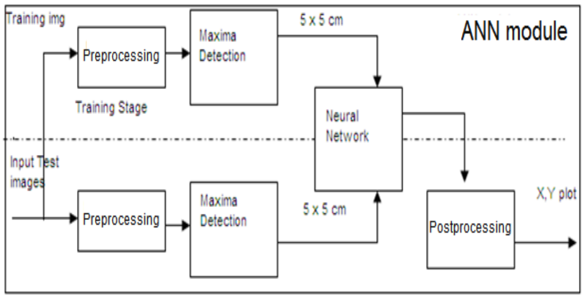

Fig. 5 – ANN processing

Pre-processing part indicates images 50×50 mm. Maxima detection denotes the recognizing of light regions inside ROI for lesion detection and ellipse will be a training sample, see Fig. 2. Post-processing phase are computed coordinates of ROI center by ANN followed by displaying ellipse in image. Simply we can describe used ANN:

- multilayer ANN with supervised learning
- patternnet ANN model in MATLAB
- learning with backpropagation (EBP) algorithm[4]
- MSE error for checking

In MATLAB we create this MLP topology with patternnet function with inputs and targets

```
patternnet(hiddenSizes,trainFcn)
```

with parameters of number of hidden layer and training function. In our case `hiddenSizes=3` and `trainFcn` is `traingdx`[5] with momentum and adaptive learning rate EBP.

```
[net,tr]=traingdx(net,inputs,targets);
```

This training algorithm is one of used modified EBP algorithm for better MSE convergency down to global minimum.

Training set S for supervised learning is given by as set of inputs and desired response (targets).

$$S=\{(I_1, D_1), (I_2, D_2), \ldots, (I_n, D_n)\}, \quad (2)$$

The desired responses D_i are given as positions of correct coordinates for ellipse. The goal of ANN module is a learning of position for different images which is based on correct SN position in input image (Fig. 3). Designed ANN is constructed as 3-layer MLP where hidden layer computes the position, more precisely coordinates. As output we get the correct ellipse to consecutive area measurement inside ROI. We use the activation function logical sigmoid which is given by

$$f(x) = \frac{1}{1+e^{-\lambda x}}, \quad (3)$$

where λ is gain of sigmoid $0 \le \lambda \le 1$; standardly $\lambda=1$.

ANN compares after each epoch of learning the error which is define as difference between targets and output from network. We can stop learn if this error is minimal. We will use MSE (*Minimal Square Error*), usually used for this model. The MSE is expressed as sum of partial differences between real results and desired response. Formally we express

$$MSE = \frac{1}{N}\sum_{j=1}^{N}(D_i - I_i)^2 \quad (4)$$

[4]http://www.learnartificialneuralnetworks.com/backpropagation.html

[5]http://www.mathworks.com/help/toolbox/nnet/ref/traingdx.html

ISBN: 978-1-61804-089-3

Therefore, total error is defined as summation of partial errors. Partial error for each j-th training sample is defined as the difference

$$E_p = D_j - I_j. \tag{5}$$

This error E_p is computed for each sample from *S*. According to this error we can observe how error is changed. The goal of ANN training is to minimize MSE. It is iterative process based on gradient method and we need to reach a global minimum of this error. MSE is graphically interpreted as learning curve. MSE < 0.01 (we set this threshold) is reached after 100 epochs of learning.

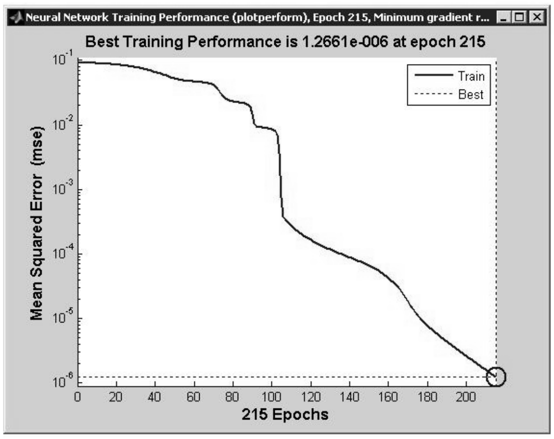

Fig. 6 – MSE error decreases with epochs

The learning is based on comparison of (*x*; *y)* coordinates of located ellipse with input samples. Output of ANN is represented by 2-D vector of (*x*; *y)* coordinates which were acquired by training. User can set a new coordinates as applicable input followed by re-training of ANN with new coordinates. These coordinates ANN inserts as a new training sample, thus we have more correct samples. Furthermore, we observe descending tendency of MSE during epochs (Fig. 6). We set the threshold value for *MSE*=0.01 given by:

if $T_{MSE} \leq 0.01$ ***then*** stop_learning ***else*** next_epoch.

Practical testing of this method showed that designed ANN is useful for positioning of ellipse in correct position in ROI window. Accuracy of this method is approximately 70% for 50 tested images. Re-training allows reaching higher accuracy for manually set of coordinates and more images as input position.

Within this practical ANN training, we work with described grayscale images and/or binary images which are obtained according to manual level of thresholding or Otsu[6] method. The following figure shows panel with buttons for loading input files (depend on US device model) and options for binary thresholding and displayed binary image.

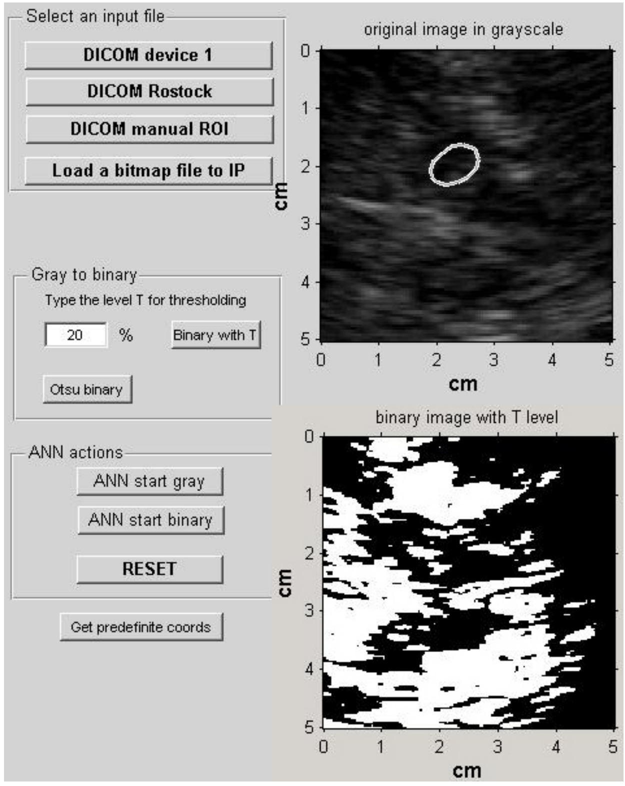

Fig. 7 – Binary image according to T level

After ANN training we will see output position ellipse and re-trained position from new coordinates. These computed positions, more precisely coordinates of center (see Fig. 9) can be saved into TXT file and may be used later to training a new samples in *S* given by formula (2).

[6] http://www.labbookpages.co.uk/software/imgProc/otsuThreshold.html

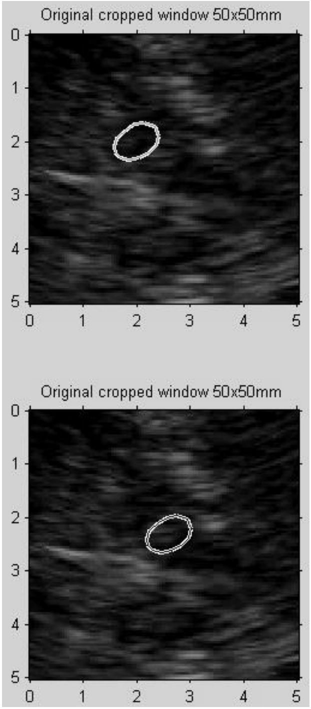

Fig. 8 – Output and new re-trained position

Our application shows the coordinates of center of ellipse and we can manual re-train ANN according to manually typed coordinates. The following figure shows coordinates and manual update to better training of ANN, we can build a set *S* with well positioned examples.

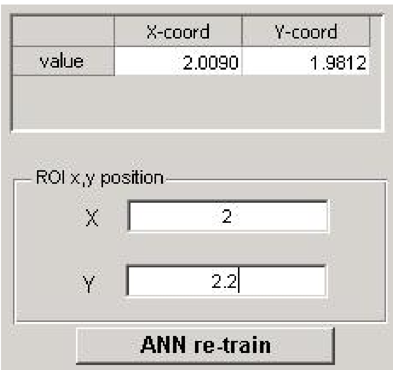

Fig. 9 – Get and set coordinates X, Y for training samples

If we will have more examples, we should reach higher accuracy, because ANN will be better trained for more input samples. Application also provides get and set coordinates for re-training of position; it is important for creating new samples for training set *S*. Generally speaking, larger set S means better accuracy for training new samples for input images.

The main goals are learning of ANN on grayscale and binary images and observe which model is better. Moreover, we can change ANN topology and observe MSE in accordance with setup of training function. In consequence of this training we can obtain an optimal solution for automatic positioning of ROI inside SN which is followed by measuring of area to PD and non-PD distinguishing.

2.4 Module area measurement

After this processing with ANN module for correct positioning of ROI inside SN, we need to compute the area of lesions (regions) for all intensities how we described in Chapter 1. The result of this module is decreasing area depend on level of echogenicity (intensity) to distinction of PD and non-PD cases, it is based on binary thresholding and using masks as ROI objects. For details about processing and statistics, see [2] and [3]. Details about reproducibility for PD diagnosis in [14]. The following figure shows the result of measurement of area. More about used statistical characteristics is available in [8].

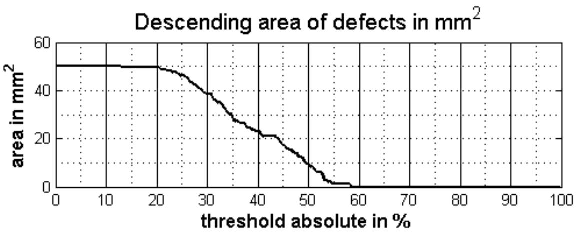

Fig. 10 – Measurement module and result of measuring

3 Conclusion

The goal of presented method was to show the image processing of ultrasound images with approach of ANN. Method is based on supervised learning of MLP and positioning of elliptical ROI inside examined SN in midbrain. Precise positioning helps to automatic recognition of ROI for different images. We observed that method is useful with relative good results, but achieved accuracy may be better with more training samples and more images. Processing with MATLAB is effective because MATLAB provides wide range of tools for image processing and neural networks.

Designed ANN MLP has been tested with different settings such as the training algorithm, number of hidden layers, etc. Training with momentum and sigmoid gain adaptation were found as useful for this case. MSE < 0.01 were reached after approximately 90 epochs of training (Fig. 6). User can manually set coordinates and add it to new training sample for re-train of ANN for better accuracy for a priori unknown images.

Measurement module provides final measuring of area inside ROI SN to distinction PD and non-PD cases. Program affords training of positioning on grayscale and binary images which can be useful for better accuracy. Also we can train ANN better with binary patterns because are simpler. Achieved accuracy is about 68-75% in comparison with erudite doctor who positioned ROI as perfect example to learning.

The future work will be based on better accuracy of ANN to automatic ROI positioning. It will be tested on larger dataset than 100 images and will be examined other ANN topologies with different learning approach. Moreover, we will focus on better learning of ANN with grayscale and/or binary images to higher accuracy, although we can never replace erudite neurologist.

This research is supported by grant SGS 6/2012.

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