The image recognition of brain-stem ultrasound images with using a neural network based on PCA

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Abstract: - This paper shows how to classify the medical ultrasound intracranial images by using PCA method. The main goal is a classification of ROI substantia nigra in midbrain. The classification of images is useful to detection Parkinson´s disease (PD). Work is based on image processing and is realized with the help of artificial neural networks which has been simulated in NeuroSolutions 6 software environment. We have selected a PCA method for processing. This method is well applicable in NeuroSolutions.

Key-Words: - ultrasound, neural network, image processing, Parkinson´s disease

1 The scope of this paper

The scope of this paper is an image processing in medicine solving problem of pattern recognition SN on finite set brain-stem ultrasound images. Paper contents theoretical mathematical background of problem and description of solving in practice. For analysis of these images we use a method Principal Component Analysis (abbreviated as PCA). Practical implementation of analysis is realized in C# programming language as a desktop application. PCA method is widely used for problems with image processing as recognition and compression. This method is the one from a lot of methods for image processing, exactly to pattern recognition where is necessary a feature extraction. Our ROI (Region Of Interest) is substantia nigra (SN) in brain-stem. More about SN in part B.

Also we will show how to solve this problem with artificial neural networks (ANN) and why we use it. The neural networks are very applicable for image processing problems. We will build a topology of ANN and simulate some cases with a different sets of images. Thus we have the different approaches to comparison.

1.1 Role of image processing in medicine

Actual modern medicine is focused on new progressive technologies and modalities for image processing and we encounter with these technologies in many areas of medicine. Nowadays we have not only traditional X-rays but we have a lot of advanced methods to detection and research without real cutting. The development of these methods is very fast and progressive. Modalities such as US, CT, MRI, X-Rays, PET are nowadays common but indispensable in medicine. This work also well shows interdisciplinary character between medicine and computing. During this work we will work only with ultrasound modality because it is the best for brain scanning.

PCA was selected because it is relative simple to understanding and is appropriate for our solution of pattern recognition in brain-stem ultrasound images. Image processing with PCA (and other methods) is also very well applicable with artificial neural networks. We can simulate neural networks to recognition and classification; it is great for neural network simulators. For a PCA is designed even special type of neural network, PCNN (Principal Components Neural Network) which is based on supervised and unsupervised part of learning and we will use it. Pattern recognition generally is appropriate to neural networks implementation equally as PCA well applicable to pattern recognition solution.

Why we use ultrasound modality to detection SN? The main benefits for ultrasound against CT are:

- no demagining influence for human as CT or RTG rays
- US is well applicable for soft tissue density (brain stem density is 34.7 HU)
- B-mode scanning is advisable in form brightness differentation to select ROI SN
- US has an importance for small areas such as SN

1.2 Neurology, ultrasound and substantia nigra

Ultrasound is the appropriate modality for neurology, brain and his parts are soft tissues. This modality is based on ultrasound detected and reflected sound waves with frequency over 20 kHz that is a threshold of human sensitivity, up to approximately 10 MHz. Cranial

ultrasound uses reflected waves to produce pictures of the brain. Our ROI, substantia nigra is a brain structure located in the mesencephalon (midbrain) that plays an important role in reward, addiction, and movement. Parkinson's disease (PD) is caused by the death of dopaminergic neurons. Main symptoms of PD include muscle rigidity, tremors and changes in speech and gait. Ultrasound imagining in neurology is also important for detection another diagnosis – encephalitis, meningitis, congenital hydrocephalus and so on.

Our classification of ultrasound images is the first step to detection of potential PD diagnose. How we explained in previous chapter, sono imagining is the best technique to displaying of SN in midbrain. If we mentioned the interdisciplinar character of this work, now we can see a position of SN in brain slice, our searched ROI in ultrasound images. The position of SN is important to understanding of ultrasound cranial images in practice. In ultrasound images SN has a butterfly-shaped area. The following image shows a position of SN in brain slice.

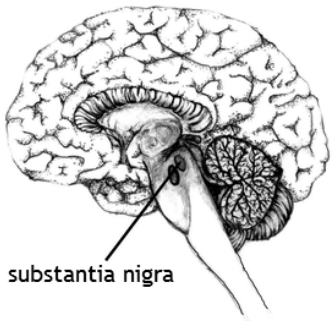

Fig. 1 The position of SN in brain

2 Mathematical background of PCA

PCA is very useful method to pattern recognition in image processing which is based on statistics and matrix algebra. In all cases we suppose discrete model of computing. In brief, we can summarize mathematical background of PCA to following steps:

- transform images to vector form (input) and compute the mean
- compute covariances among vectors and construct a covariant matrix
- from covariant matrix get eigenspace – eigenvalues and eigenvectors
- assess an optimal threshold T for choosing the K largest determining components

Generally PCA is a transform from correlated data to other uncorrelated data and dimensionality reduction.
At the first step we must express each image as a *vector* of equal size. Each 2-D image is accordingly represented like a 1-D long vector pixel by pixel of brightness values. Images from ultrasound are naturally in grayscale (R=G=B) and we will get vector of brightness values. It is a general input to PCA. Each vector has the following form

$$v_i = (x_1, x_2, \dots, x_{mxn,}), \tag{1}$$

where index i is i-th images in set and mxn is a resolution of image. Number of vectors is number of images in collection. Second step is the computing centered data, from each vector is substracted the arithmetic mean of each vector (dataset). We will need it to compute covariances. Formally we express

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{2}$$

Next processing will be focused on computing of covariances and from these covariances we construct a covariant matrix. This step is critical for next parts. From definition of covariance follows that covariant matrix is real and symmetric. In probability theory and statistics, *covariance* is a measure of how much two variables change together. Covariance is a kind of variance for 2 or more datasets (vectors). Variance is only for 1 dataset and covariance is simply extension for 2 or more sets. Covariances are symmetric too, exactly expressed by $cov(X, Y) = cov(Y, X)$ for datasets X and Y. Thus covariance for n finite number of datasets is denoted by

$$cov(X_1, X_2, \dots, X_n) = \frac{\sum_{i=1}^{n}(x_{1i} - \overline{X_1})(x_{2i} - \overline{X_2}) \dots (x_{ni} - \overline{X_n})}{n} \tag{3}$$

where $X_1, X_2, \dots X_n$ are datasets, x_i and are i-th item from X_i dataset, n is number of images. X_i is the arithmetic mean (Equation (2)) of X_i dataset. For example, if we have only 2 datasets X and Y, then we compute cov(X,X), cov(X,Y), cov(Y,X) and cov(Y,Y) to covariant matrix. Simply we can extend it to more datasets than two, generally n datasets. In our experiment, we will work with 10 or 20 vectors. We manually proved that covariances are really symmetric. The covariance is also used for a correlation coefficient in neural networks to compute MSE (*Mean Square Error*). Correlation coefficient is the one of the most important indicators in statistics. Important fact is that covariance matrix has identical dimension like input

vectors. Zero covariance would indicate that the two variables are independent of each other.
PCA is based on computing of *eigenspace* that is eigenvalues and corresponding eigenvectors. We constructed covariant matrix and now we can compute the eigenspace. Because the covariant matrix is real and symmetric, we can simply compute an eigenspace. Number of eigenvalues is equal to number of input vectors. In practice, if we have 20 input vectors (images), then covariance matrix has a dimension 20x20 and so 20 eigenvalues with their corresponding eigenvectors. Computed eigenvalues are in descending order, $\lambda_1 > \lambda_2 > \ldots > \lambda_n$. In chapter III we will see it practically. We issue from properties of covariant matrix such as symmetry and *n by n* matrix type. Generally to computing the eigenspace from matrix *Cov*, matrix must accomplish the following criteria (last criterion is especially for PCA implementation):

- is symmetric
- is real and squared
- contents equal number of rows as images

In other words from this covariance matrix we compute the eigenspace - λ_n nonzero eigenvalues and their corresponding eigenvectors. If we denote covariant matrix as *Cov* and exists a scalar $\lambda \in R$ then we compute eigenvalues of covariant matrix from the following equation:

$$Covu = \lambda u. \tag{4}$$

Where *Cov* is real covariant matrix, *u* is nonzero vector with n-dimensionality from dimension of *Cov* and λ is eigenvalue. A set of all eigenvalues λ is a matrix spectrum. From this spectrum we will select the first best K eigenvalues with corresponding eigenvectors how we will describe in the following part.
The last step is critical, we must choose the first K largest components what are the most important – separation helpful signal and noise, in our case a classification of images. We must accomplish it very thoroughly. In our goal is the detection of ROI (*Region of Interest*). Threshold for selected components is variable but commonly 0.9-0.95. Mathematically is threshold expressed by the following inequality

$$\frac{\sum_{i=1}^{K} \lambda_i}{\sum_{i-1}^{N} \lambda_i} > T \tag{3}$$

where in numerator is sum of the first K eigenvalues, in denominator is trace of matrix (total sum of N eigenvalues) and threshold. Generally, extremely small or high threshold could be insufficient to select components.

3 Practical implementation and results

This chapter is fundamental for our research. Contents a description of own work and results. The goal of practical implementation is a PCA processing of neurosonographical brain-stem images where we find substantia nigra. Our practical result is a classification of images with SN. The following image shows a position of substantia nigra in brain stem on ultrasound image.

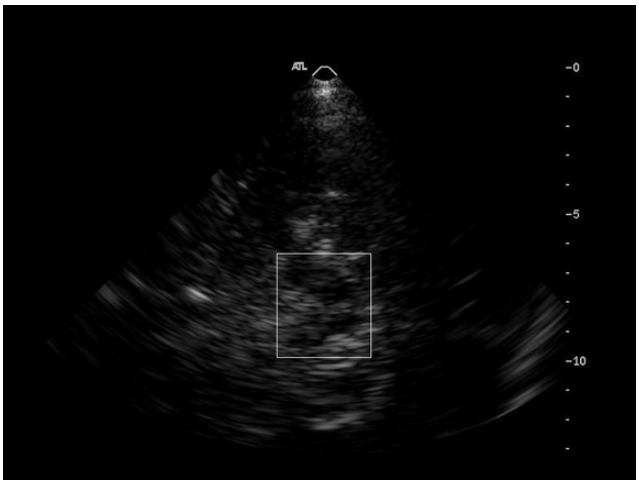

Fig. 2 A highlighted position of SN in brain stem ultrasound image

3.1 Image pre-processing

As input we have a collection of ultrasound intracranial images with different level of SN visibility. The main processing to neural network application is based on noise reduction. Before all editing we deleted text data apart from scale on right side.

The noise reduction in ultrasound images is problem because we must reduce a dynamic speckle noise which is typical for ultrasound imagining. Ultrasound images are very sensitive by form to dynamic speckle noise. The speckle noise arises from different tissues and actual position of ultrasound probe. The main problem for reduction is that speckle is not static noise but dynamic in image.

The next pre-processing step was cutting images to smaller size 200×200 pixels from the same seed pixel with ROI SN. It is good for work because images are smaller as input to ANN. For PCA application we distinguish that all images have the same resolution. If we have these small images then influence is not very considerable despite speckle noise should be reduced. In the original images is speckle noise distinct in different

parts of image. It is dynamic and depends on probe position. Fortunately we found a small application for speckle noise reduction with adjusting of sensitivity. This software is advisable for ultrasound.

Because we got input data as JPEG images converted from original DICOM format, the last step of pre-processing was the conversion 24-bit RGB JPEG images into 8-bit JPEG images. Because ultrasound images are naturally in gray scale, we can convert images into 8-bit gray scale. For each pixel intend that R=G=B and we can express each pixel as only one intensity value H. Generally it is expressed by the following formula:

$$R=G=B \Rightarrow H \in \langle 0; 255 \rangle.$$

Now we comprehend each image as real matrix with intensity values H_i (i-th pixel).
After all steps of pre-processing we got the input images in the following format (8-bit JPEG, 200×200 ROI SN)

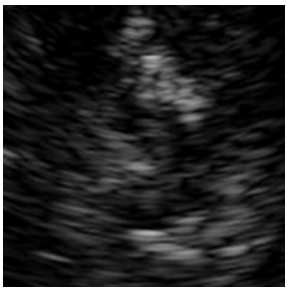

Fig. 3 ROI SN on 200×200 image

We used own C++ algorithm which has been developed in IDE Dev-C++ which generates input vectors that contents pixel by pixel intensity values. Input to algorithm is 24-bit RGB images and output is TXT file of $\boldsymbol{v}^T$ vector of intensity values. Why only 1 value? Because ultrasound images are naturally in gray scale, that R=G=B => only one intensity value of each pixel from range ⟨0; 255⟩. This is a primary input to PCA as in equation (1).
Our own algorithm has three parts – reading image to memory, converting into vector and save it in TXT file. We load all images directly in source code, processing is displayed in console window. It is the first phase after pre-processing. We will use this image vector in all cases. This algorithm is fast and simple.

Now we can simply summarize the steps of our image pre-processing phase:

- deleting a metadata (converted from DICOM)
- cutting to smaller resolution 200x200 pixels
- speckle noise reduction
- converting image matrix into TXT column vector file

3.1 Practical results of PCA

This section of paper is fundamental, contains real practical results, comparison and conclusions.

In our collection of images unfortunately we have only approximately 25 images with well displayed substantia nigra. But it is better for recognition we can apply an image classification to potential diagnosis. Corrupted substantia nigra is the feature of Parkinson´s disease (more information in chapter I., section B).

All own practical implementation we will show with 20 images which we manually selected and classified. Ten images with well visible substantia nigra and 10 with corrupted or invisible. On this set we will follow up the changes of eigenspace..

All our results has been processed with both applications which we described. It is necessary to validate of correctness of results.

3.1.1 Outputs from Gnumeric spreadsheet

In the first case, we computed PCA with the help of Gnumeric spreadsheet which contents statistic functions including PCA. We stored generated vectors into XLS file and we got a set of input column vectors how we described. This input is basic for computing. Gnumeric is running under Ubuntu 10.04. From menu Data we picked up Principal Component Analysis, marked area (all input) and run it. We got output in form covariant matrix and eigenspace that eigenvalues and eigenvectors which are principal components.

3.1.2 C# application Principal Component Analysis

Our fundamental solution for the first part yields software which is on the web free to download with source code. Fortunately it is freeware and open-source solution. We downloaded it from website which is in list of web sources.

It is great WinForms C# software to calculating of all needed results. We optimized this SW for faster computing with large inputs that was described in previous chapter. The main benefit of this application is a possibility change and optimize algorithm against Gnumeric which includes PCA as built-in function. This C# based application is used for our main research, to classification.

For each case we have worked with the same inputs. What is very important is proof that Gnumeric and this software gave equal output. We have a control that our results are OK. Equally as Gnumeric, basic input to PCA are vectors of images in XLS format. In addition we implemented reading a XLSX new format. In comparison with Gnumeric, results from this application

are more detailed. Gnumeric has been used for control of desired output.

3.1.3 Correlation analysis

After PCA application also we need to know a correlation analysis between images. Hence we compared the correlation coefficients in mixture of images. The following graph shows correlation coefficients for desired image with visible SN to the other images. Correlation coefficients are very small because a histogram is different.

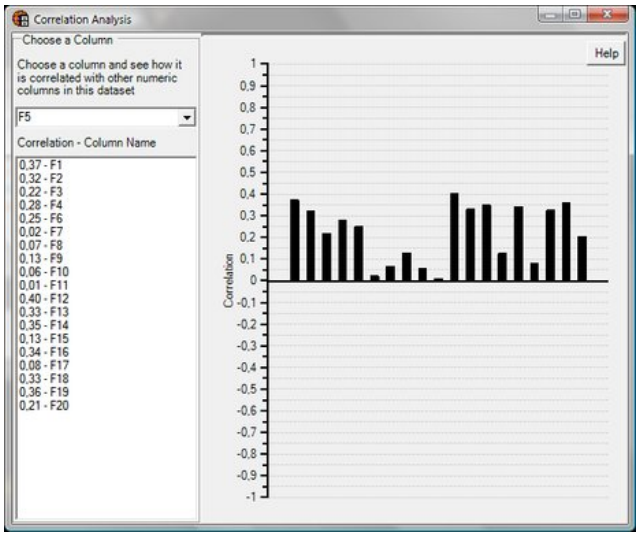

Fig. 4 Correlation analysis between different datasets

3.1.4 Eigenspace results

The main goal of our practical implementation is an eigenspace output and threshold to selection components and image classification. In pre-processing phase we manually classified images to recognition. We tried to get output for 10 images with visible nigra, 10 with invisible and compared it. It is good, but our primary output is for the mixture of images and their classification.

As input we have 20 images in form column vectors in MS Excel file and we loaded into C# application. We got centered data and output in form as eigenspace and component distribution. Now we present the eigenvalues descending order in graph (Fig. 5) and computed values with highlighted eigenvalues for threshold 0.9.

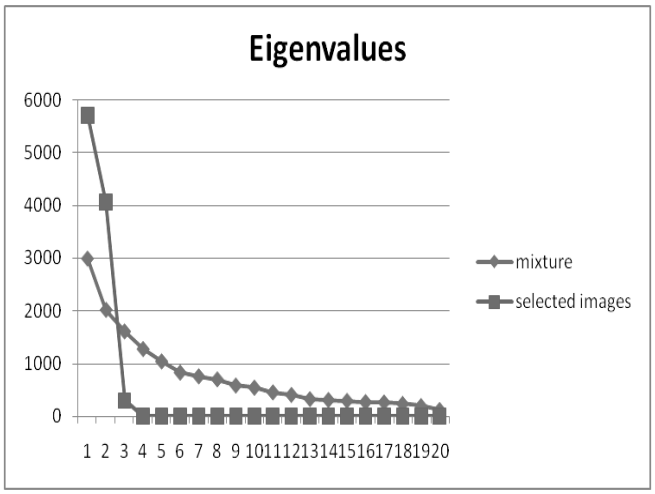

Fig. 5 Our descending order of eigenvalues

Now after we computed an eigenspace, we must appoint a threshold for useful eigenvalues and their corresponding eigenvectors (components). Also we need a proportion of eigenvalues. In our practical experiment with different sets of input images we ascertained that we need 14 first best principal components.

We computed by expression (4) described in chapter II that for our case is suitable threshold $T \geq 0.9$. This threshold is used for a selection of components. If we appoint $T = 0.9$ we will get 70% of total calculated eigenvalues which are needed for PCA processing (14/20) with minimal loss. In the case if we appoint threshold T=0.95 then we will get 18 suitable eigenvalues what are important to success.

In second case we computed the eigenspace only for the best ROI classification and we got an ouput that is the first component more than 56% proportion. Consequence is that we selected the most representative for all dataset (graph in Fig. 2).

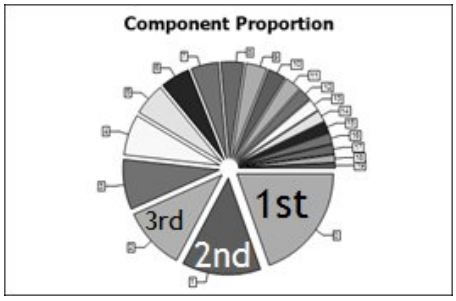

Fig. 6 Components distribution

From this graph we can see that first component is almost ¼ of all components, exactly we obtained 23.8%. In the second case when we tested representative images, we got a result of proportion 56.7% for the first

component. Also we tried to this dataset add one image from different set and this image is not important to proportion. It demonstrates changes (less than 3%). The most important fact is for which image is the largest component. From our practical experiments with application we got that the first component is ever from one set of images and next first best components are from the same set. It is a classification of images what we needed from image mixture. The main goal was appoint the threshold T for the first best K components (we calculated manually and with application we modified code) and second was classification.

4 A neural network application

Now we will simulate this problem with artificial neural network (ANN). In our case we will use NeuroSolutions software by NeuroDimension, Inc. The image recognition is well applicable problem for ANN using. In this case, we will work with PCA-based ML ANN. Furthermore we will compare the previous results with outputs which provides PCA-based ML neural network. Detailed information about ANN theory are available in references [2] and [5].

4.1 ANN topology for solving

The topology is based on ML hybrid neural network with PCA model. This type of ANN is based on supervised and unsupervised learning that is optimal for image processing, process of learning with good learning rate. The following scheme demonstrates a basic topology PCA-based ANN with Sanger´s rule for unsupervised learning. Also we have tried change it to Oja´s rule.

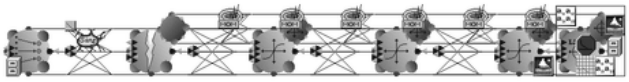

Fig. 7 A ML PCA-based ANN scheme

This figure shows the general topology of PCA multilayer network with 2 hidden layers, Sanger´s rule, image input and output and *sigmoidal* activate function. We can change all parameters for ANN – unsupervised learning, number of hidden layers, activation function, we can modify to genetic algorithms, number of principal components and so on. We use *NeuralBuilder* module in NeuroSolutions.

4.2 PCA modeling and learning

The following part will describe how we have constructed the ANN and learning. After we built the topology described in previous part, we can approach to practical modeling. As data we also use TXT vectors of images. In *NeuralBuilder* wizard we must defined an input file and desired response file. As input we use a mixture of image like a previous model in C# and Gnumeric application. For comparison with results in C# application we need to test the same set of images with some modifications, e.g. Oja/Sanger´s rule, numbers of hidden layers, number of principal components, activation function, etc. The correlation coefficients which are showed in Figure 3 were built in NeuroSolutions too, in *DataManager* module. From this DataManager we can start a modeling of ANN. In modeling also we can display a confusion matrix.

Our testing contents different tests with selected datasets and variable number of PE´s (Processing Elements), it is number of neurons in layer. In NeuralBuilder is possible to change it in each defined layer. The main goal of this modeling is the classification based on PCA statistics. Also we have compared results. We used the following modifications for ANN:

- different datasets
- changing of number of PE´s in topology
- changing of topology and learning rule

With these modifications we followed up a behavior of ANN and classification results. In basis we used ML PCA-based ANN. For different modifications we followed up the MSE between desired and real output. The optimal is $MSE < 0.02$.

4.3 Practical results

With NeuroSolutions we simulated a lot of variations of ANN as we described in previous chapter.

In this chapter we will describe results from these different variations. The best result with minimal MSE < 0.01 gives PCA-based neural network with Sanger´ unsupervised rule. With Oja´s rule (Sanger´s rule is modification of Oja´s) the results are not the best. Generally, the best result gives this topology ML ANN with Sanger´s rule with 2 hidden layers. We set 200 training cycles for learning and also followed up the learning curve (learning rate). So we can set a threshold for stop for exact value of training cycles. Now we need to optimize it for different variations.

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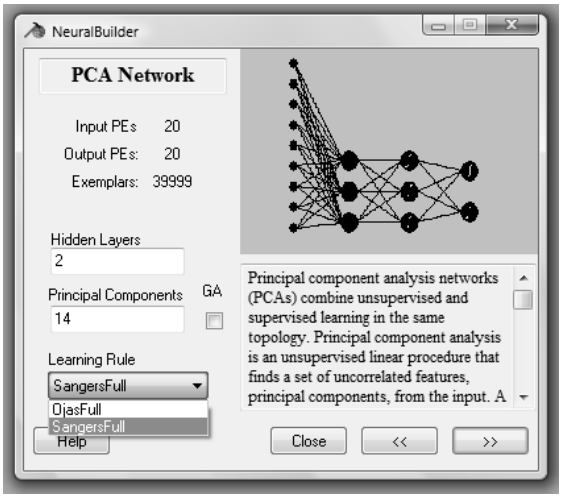


Fig. 8 Building topology of PCA ANN in Neural Builder

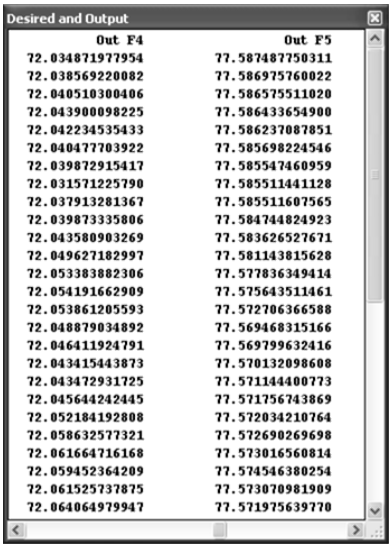
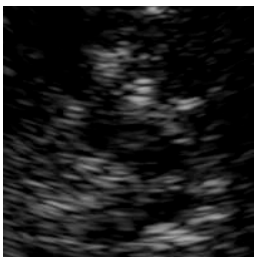


Fig. 9 Desired and output recognition

Which optimization we need? For the best learning rate and classification. The main goal is a classification of images from input file and desired file and searching of acceptable learning rate Also we can modify number of Principal Components, in our example we set 14 (from T threshold computing). We need a minimal MSE too, for this example is *MSE < 0.015* that is acceptable. In desired file we set the images with visible SN and as input we have a mixture of images that we computed in previous research. So, we need to compare C# software and NeuroSolutions with ANN. ANN is generally convenient for its. In *NeuralBuilder* module we can obtain a PCA-based ANN topology very simply. In practice we detected that classification is very similar to C# application. As we described, model PCA-based with 2 hidden layers gives the best results. In other words as the best gives same images as C# application with good learning rate. This process of learning is addicted to computer.

We tried to learn with a lot of combinations of input file. If we set same as input and desired, MSE is zero and no learning is needed. From training data (visible SN images) ANN classified input images and the most corresponding images are images with excellent visibility of substantia nigra. These images are displayed in conclusions. The following figure shows the success of recognition in percent for images that we got from C# application. It is for images with well visible SN and demonstrates success in percents.

The following Figures (10, 11) shows these images from dataset.



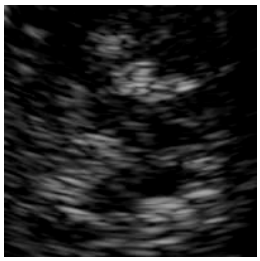


Fig. 10, 11 The best recognized images with SN

After more cycles success is ascending. As we described, we set 200 cycles for learning, but general more cycles is not important to advancement. The following images shows which topologies we tried.

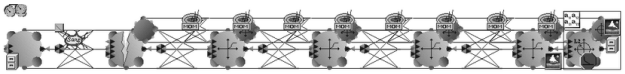


Fig. 12 PCA ML with 3 hidden layers

More of hidden layers are not primary to advancement, only faster learning.

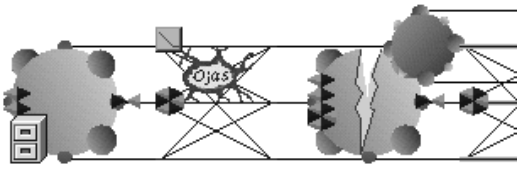


Fig. 13 Oja´s learning rule, 2 hidden layers

This type of ANN is equal as previous, but we set Oja´s unsupervised learning. Input is equal. Oja´s rule for

PCA-based ANN gives worse results than Sanger´s, worse learning time.

In practice we tried a lot of another types of ANN (number of hidden layers, rules, number of cycles and so on). In all cases we use input PE´s = input images. As activate function we use sigmoidal function which is expressed by:

$$P(t) = \frac{1}{1 + e^{-t}}. \tag{5}$$

This function is often used in ML topologies. Certainly in NeuroSolutions we can work with other functions. Also we followed up how learning is stopped. We manually set the threshold 0.015 for MSE, that is acceptable for this using. In practice we followed up that MSE was stopped after approximately 150 steps of learning on training set in the best configuration – Sanger´s rule and 2 hidden layers. With more hidden layers learning is not more effective only maybe faster for *MSE = 0.015*. The MSE is expressed as sum of partial differences between real results and desired response. Formally we can express

$$MSE = \frac{\sum_{j=0}^{P} \sum_{i=0}^{N} (d_{ij} - y_{ij})^2}{NP} \tag{6}$$

The total error of neural network is sum of partial errors which is in each training epoch. Now we can see the learning rate and MSE curve in processing.

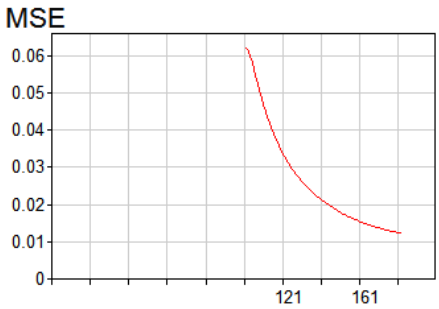


Fig. 14 MSE after 100 epochs

For example the following Figure shows MSE learning curve for only one hidden layer. MSE almost does not descend.

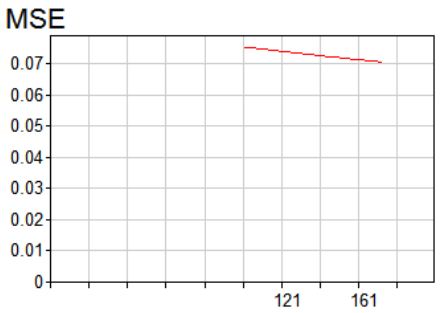


Fig. 15 MSE for 1 hidden layer

In practice with one hidden layer is not appropriate because error is too big (*MSE > 0.05*) after more than 300 epochs. It is not acceptable. NeuroSolutions also shows MSE and normalized NMSE in real time in progress, both measures shows the error on output Normalized MSE (NMSE) is derived from MSE divided by variance. NeuroSolution also displays MSE and NMSE in pop-in window.

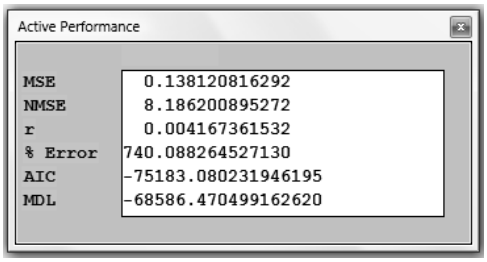


Fig. 16 MSE, NMSE in NeuroSolutions

Figure (14) shows how the learning curve descends to minimal *MSE = 0.01*. After 200 epochs it is achieved. The first phase is unsupervised Sanger´s learning, in second phase (100 steps) is supervised learning to desired response. On Figure (9) we can see success in percents for the best images.

We progressively changed the training set of images despite as pattern always proposed the images with visible SN. The main goal is classification – learning network to output. As desired response we set representative images with possible diagnosis of PD and trained network to classification.

5 Conclusions and future work

This paper showed principles of modeling neural network for image processing based on PCA method. Detailed description of PCA and all results are available in full paper. The future work will be based on ANN too, maybe with different method or approach. We have checked this simulation in Matlab software with appropriate Neural Network Toolbox. Matlab allows project compile as C++ application. Now we have

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modeled ANN in NeuralSolutions which have built-in PCA-based neural network topology. The SN recognition is the important process in sonography to potentially PD diagnosis. To successful recognition we need a lot of experimental data, from different sources. We get experimental data continuously. Now we tested one set. The future work is based on processing of another data. Future work also will be based on detection of defects in SN ROI by region growing method with automatic detection of ROI from whole image to more exact PD diagnose and furthermore we can use some filtering methods. In our experiments we achieved success up to 80% of classification. The interdisciplinar character of this work is apparent in context of informatics in medicine.

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