Pilot Design of a Rule-Based System and an Artificial Neural Network to Risk Evaluation of Atherosclerotic Plaques in Long-Range Clinical Research

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Abstract. Early diagnostics and knowledge of the progress of atherosclerotic plaques are key parameters which can help start the most efficient treatment. Reliable prediction of growing of atherosclerotic plaques could be very important part of early diagnostics to judge potential impact of the plaque and to decide necessity of immediate artery recanalization. For this pilot study we have a large set of measured data from total of 482 patients. For each patient the width of the plaque from left and right side during at least 5 years at regular intervals for 6 months was measured Patients were examined each 6 months and width of the plaque was measured using ultrasound B-image and the data were stored into a database. The first part is focused on rule-based expert system designed for evaluation of suggestion to immediate recanalization according to progress of the plaque. These results will be verified by an experienced sonographer. This system could be a starting point to design an artificial neural network with adaptive learning based on image processing of ultrasound B-images for classification of the plaques using feature analysis. The principle of the network is based on edge detection analysis of the plaques using feed-forwarded network with Error Back-Propagation algorithm. Training and learning of the ANN will be time-consuming processes for a long-term research. The goal is to create ANN which can recognize the border of the plaques and to measure of the width. The expert system and ANN are two different approaches, however, both of them can cooperate.

Keywords: Atherosclerotic plaque · Ultrasound · Expert system
Rule-based system · Image processing with ANN · B-image recognition

1 Atherosclerotic Plaques, Their Risk and Measurement

In general, atherosclerosis is one of the most important causes of mortality. Early diagnostics and prediction of atherosclerosis is a key part of modern medicine.

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This paper has two parts. The first part is focused on a design of rule-based expert system which can be used for decision what next steps are needed depending on progress of the plaque. This system is based on defined rules as a decision-making system. Designed expert system should be a valuable tool for evaluation of the progress of the plaques during series of examinations. Early diagnostics of the plaques and reliable evaluation of their progress are two different, but closely related parts to avoid needless death and for starting the most optimal treatment as well. The second part of the paper is devoted to design of a model of artificial neural network (ANN) which could be able to recognize border of the plaque. ANN should be designed as a feed-forward model with Error Back-Propagation algorithm. In this paper an idea how to create ANN with supervised learning as one of many types of neural network models designed for image processing is discussed.

2 Input Data

For this study a set of measured width of the plaques from total of 482 patients is used. This is a long-term study; each patient was examined for 5 years at regular intervals of 6 months. In this study the data of width of the plaques measured from B-image is used, see Fig. 1. More detailed description of principles of B-imaging of the plaques is available in [1] and a general view of image processing approaches in medicine is available in [2].

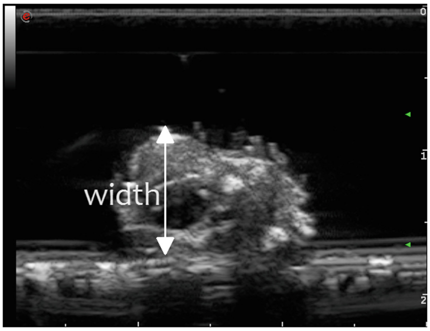

Fig. 1. Measured width of the plaque on B-image

There are different progress models of the plaque during long-term study according to stored data:

- stable plaque with no significant changes
- stable plaque with regular increasing/decreasing, no peaks
- unstable progress of the plaques, peaks
- highly unstable plaques with many peaks and extreme changes between examinations

These four progress models are a starting point for definition of exact rules for the expert system.

3 Design of Rules Used in the Expert System

Input data represent width of the plaque measured from left (L) and right (R) side at regular intervals of 6 months, see Table 1.

Table 1. An example of measured width of the plaque for 4 patients

side / measurement	1	2	3	4	5	6	7	8	9	10	11	12
L	4.6	3.6	4.7	4.1	4.6	4.2	4.9	4.3	4.3	4.3	3.9	4.1
R	3.6	2.5	3.2	3.2	3.4	3.6	3.8	3.9	3.8	3.8	3.2	3.2
L	2.7	4.3	4.1	4.0	4.8	4.8	4.8	5.7	5.7	4.2	N/A	N/A
R	3.1	4.2	4.2	4.2	4.3	4.5	4.5	3.4	5.0	5.5	N/A	N/A
L	3.3	2.3	2.2	2.6	2.2	2.5	2.5	2.7	2.7	2.7	3.4	3.6
R	3.0	3.0	2.5	2.3	2.8	2.7	2.7	2.5	2.5	2.5	2.5	2.7
L	2.0	2.4	2.4	2.3	3.4	2.6	2.6	2.6	2.6	2.6	2.6	2.7
R	4.3	4.3	4.3	4.3	4.3	4.3	4.3	2.8	3.4	3.3	3.3	3.7

Highlighted measurement was visually judged as erroneous. Let t_1, t_2, t_3,...t_n where $n = 10$ is a series of an examination during 5 years at regular intervals of 6 months. The principle of this system is based on using IF-THEN rules from which the final consequent is decided; it is a rule-based decision system which can be briefly described as follows. The rules are based on the four following criteria:

- maximum and minimum value from all measured data
- difference Δ_t is not considered in absolute value; if $\Delta_t < 0$ width increases and if $\Delta_t < 0$ width decreases
- number of occurrences of difference below or under threshold value
- trend of the progress for 4 consecutive measurements (increasing or decreasing)

The difference Δ_t is not considered in absolute value, thus if $\Delta_t > 0$, the plaque width is growing and if $\Delta_t < 0$, the width of the plaque is decreased.

The expert system is designed using the following exact if-then rules:

- Rule A: IF $\max(\Delta_t) > 2$ mm THEN $ModerateRisk$
- Rule B: IF count of $\Delta_t > 2$ mm at least 2 THEN $ModerateRisk$
- Rule C: IF $\min(\Delta_t) < -2$ mm THEN $ModerateRisk$
- Rule D: IF count of $\Delta_t < -2$ mm at least 2 THEN $ModerateRisk$
- Rule E: IF at least of 4 consecutive differences $\Delta_t < 0$ THEN $ModerateRisk$
- Rule F: IF at least of 4 consecutive differences $\Delta_t > 0$ THEN $HighRisk$

– Rule G: IF $\min(\Delta_t) < -0.8$ mm $\wedge$ $\max(\Delta_t) < 0.8$ mm THEN $LowRisk$
– Rule H: IF no previous rules are applied THEN $LowRisk$ (the plaques with no peaks)

So, there are 3 options (output variables) for recommended steps:

– $LowRisk$ - no immediate steps are recommended
– $ModerateRisk$ - check the plaque progress
– $HighRisk$ - check if the measurement is correct (no error), immediate recanalization is strongly recommended

The following rules union produces:

– $A \wedge B$ THEN $HighRisk$
– $E \wedge G$ THEN $LowRisk$
– $F \wedge G$ THEN $ModerateRisk$

The inference engine of the system is designed to produce a reasoning on the rules. In Table 1, there are examples of reasonings. In the past, we have designed a similar expert system to evaluation of substantia nigra hyperechogenicity and the results were published in technical papers [3–5] and also in clinical studies [6,7] (Table 2).

Table 2. Output variables and their reasoning

Variable	Comment
LowRisk	no immediate steps are needed, the plaques seem stable
ModerateRisk	check the progress which could be starting point of a problem
HighRisk	critical growing of the plaque, high risk of stenosis and rupture

However, a sonographer can set more rules, their relations and reasoning; the system is extensible and modular.

4 Evaluation of the Outputs

According to outputs of the expert system immediate recanalization should be recommended. The next step is to verify the reliability of the designed expert system with experienced sonographer. Consider the following example. Let

$$3.1; 3.8; 3.8; 3.8; 3.8; 3.0; 3.0; 3.8; 2.4; 4.1; 3.2; 3.8; 3.8; 3.8; 3.5; 3.6; 3.8$$

be input data of measured width into the system. Maximum difference is 1.7 mm, the minimum difference is -0.3 mm. The plaque does not have at least 4 consecutive differences higher than 0. The Rule H is applied because there are no significant peaks and extreme differences.

In the second example:

$$3; 2.9; 2.8; 2.8; 2.6; 2.6; 2.6; 5.2; 5.2; 5.3$$

the obvious maximum difference is 2.6 mm. The Rule A is applied and the plaque is evaluated as moderately risk ($ModerateRisk$).

4.1 Adaptable Rules to Quality Improvement of the Results

One of the main advantages of this system is adaptability to improving quality of results for more reliable diagnostics. The rules can be modified and/or add new rules. Thus, adding and modifying rules can be useful to create the expert system with high accuracy supported by an experienced sonographer. Another way is to create adjustable expert system; a user can modify rules depending on measurement, e.g. set for high resolution, low resolution, different gamma correction, etc.

5 Using Neural Network in Long-Range Research

The designed expert system should be a helpful software tool to evaluate progress of atherosclerotic plaques using set of IF-THEN rules to decide next steps, i.e. treatment, immediate recanalization, etc. All results must be analyzed by an experienced sonographer. If the system is considered reliable, the next step should be to create a model of artificial neural network (ANN) as a learning platform which will be adapted depending on training set with many examples of outputs and desired outputs. It is a second phase of this study and the second approach; different from Decision-Making expert system. In 2016, the authors published a paper focused on the idea of different approaches how to detect atherosclerotic plaques in B-image [8].

5.1 An Idea How to Design ANN to Classification of Risk of the Plaques

The idea of the ANN is different from the principle of the expert system. The input data are B-images with displayed atherosclerotic plaques in different progress of the plaque instead of stored numerical values. The goal of the ANN is to learn how to classify the plaques according their width and other features. On Fig. 1 the width of the plaque is displayed There are key questions:

- What features should be used?
- How to determine plaque from the artery wall?
- What accuracy of the ANN is acceptable for clinical studies?
- How to define training set to classification learning?

We have the following idea of ANN architecture:

– a feedforward multi-layer network with supervised learning
– Error Back-Propagation algorithm to minimization of the global error
– developed in MATLAB (with NN Toolbox) [9] or similar software for ANN modeling

Figure 2 shows an example of the ANN which could be used.

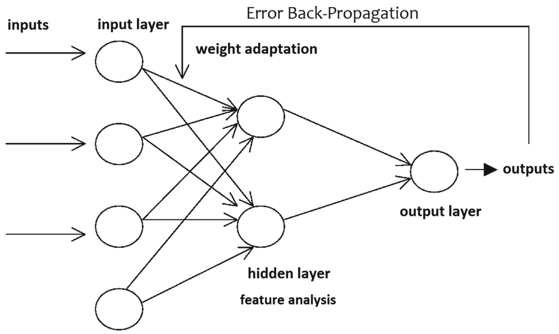

Fig. 2. ANN model with Error Back-Propagation principle

The input is B-image on input layer, each input is multiplied by a weight w; j-th input is multiplied by weight w_j. The principle of the idea is based on weight modification depending on computed network error. The learning of the network is based on comparison of the error for each input.

$$PE = y_j - d_j$$

where y_j is a real output and d_j is a desired output for j-th input. Global error is the sum of all partial errors. Thus, when the large set of examples in training set is available, the network could learn a lot of cases of plaque types. Crucial problem is to determine features which could be used to compute width of the plaque for final output. Designed ANN has the following properties:

– **input** in form of the matrix $m \times n$ of digitized B-image with detected edges
– **hidden layers** computes edge detection algorithm and visibility of the plaque
– **output layer** has 4 neurons to classification the plaque (no visible plaque, low risk plaque, medium risk plaque and high plaque) similarly to output of designed ES

Edge Detection. Images are preprocessed using edge detection. The network is designed to evaluate plaques using features from edge detection.

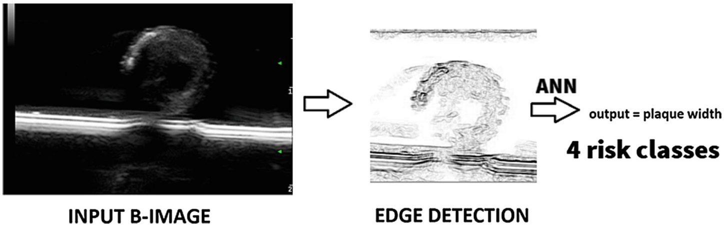

Fig. 3. Input B-image, extract edges with inverted colors) and the output to risk classification

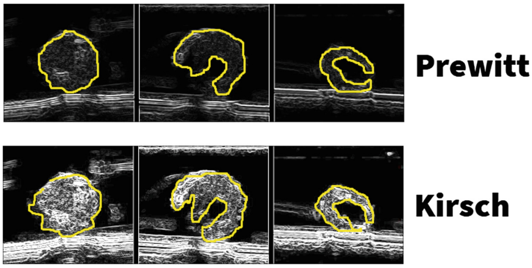

Fig. 4. Prewitt and Kirsch operator with bordered edges to training the network

Edge detection could be an efficient way how to recognize the border of the plaque to measurement of width and evaluation of the risk. There are two major problems:

- isolated pixels which can be considered as a part of the plaque
- artery wall can be also considered as a part of the plaques

Kirsch or Prewitt operator could reach well-bordered shape for training and learning process. On Fig. 4 Prewitt and Kirsch edge detection with border is applied on images from Fig. 3.

Training and Learning Process. The principle is based on a training set in which the input-desired output pairs are paired, i.e. for each input the desired output to learn the network is known. The training set should be supplemented by new examples. The learning of the network is based on error minimization depending on an improvement of the training set. A sonographer must determine error threshold for acceptable accuracy. To determine network error MSE (Mean Squared Error) is used in many applications to learn accuracy evaluation of the network. For simplification, the following preconditions are required:

- all images with the same resolution, zoom level and section
- all images from the same section, e.g. cross-sectional
- all images have the same zoom level

Nevertheless, the design of the ANN is a time-consuming process till the network is useful with reliable results for clinical studies. The most difficult part is selection of the most appropriate features in B-images due to many different types of the plaques caused by fibrosis, calcification, inflammation and other factors, see Fig. 5.

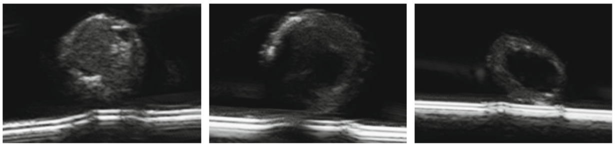

Fig. 5. Different types of the plaques on B-image

The Goal of the Learning. The goal of the learning process is to minimize the network error. For each input desired output is assigned. It is computed partial error PE and the global error. The training set contains well-bordered plaques of many types. The goal is to learn ANN to recognize border and measure width depending on scale axis. To reach better accuracy the training set is supplemented with new examples. When global error is lower than a determined value, the learning process is ended and ANN will work with required accuracy.

5.2 First Experimental Results with ANN

As the first step, we constructed a simple feed-forward ANN with implemented algorithm to border detection. We used a set of 20 images with significant plaque and for each image well-bordered plaque shape determined by experienced sonographer was used. When testing, we use these images to check if the border as output from ANN is considered as well or not to correct classification, see Table 3. The results represent the first run of the network without training/learning process with a large set of patterns.

Table 3. Experimental first results using untrained ANN

Edge/image	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Prewitt	T	T	F	F	T	T	F	F	F	F	T	T	F	T	F	F	T	T	F	F
Kirsch	T	F	F	F	F	T	T	F	T	F	F	T	F	T	T	F	F	F	F	T

where T (true) is an acceptable result and F (false) is a rejected result by sonographer. Correctness of edge detection is key for reliable risk classification of the plaque. Untrained ANN shows error rate $> 50\ \%$ for both edge detection operators. It is strongly unsatisfactory for a clinical study. The aim is to train the network to reach reliability > 85 % with determined partial error between each output and desired output. To training the network we need to use at least 482 B-images from which the data for designed expert system is extracted. Edge detection must be trained to recognize the shape of the plaque and how to separate artery wall, see Fig. 6. Brief description of the functionality of the ANN model:

– input $m \times n$ neurons according the image resolution
– transfer function is logistic sigmoid
– initial uniform weight distribution
– 100 epochs of training

Until the accuracy is not reached, ANN must be modified (weights, number of hidden layers) or another ANN architecture must be used [10], e.g. convolutional neural network (CNN) based on deep learning using GPU acceleration [11]. CNN could be a very perspective solution how to recognize shape of the plaque but it is a time-consuming problem. There is also possibility to use fuzzy neural network FUZNET [12] which could be used as fuzzy-neural system for classification of the plaques. However, after trying many ANN models could be decided that the plaques cannot be recognized with adequate accuracy.

5.3 Cooperation of the ANN with Expert System

Even though the expert system and the ANN are considered as different approaches, these systems can be closely related.

– designed ES is focused on evaluation of progress risk of the plaque from measured data for 5 years
– designed ANN is focused on recognition of the plaque on B-image and evaluation of the risk based on edge detection (width of the plaque)

When the risk level is decided by using expert system, the same plaque can be compared by output from ANN (concordance of measured width).

6 Conclusions and Future Work

This study is focused on application of two different approaches in neurology for early diagnostics of atherosclerosis. The first part is to design rule-based expert system focused on decision of risk level of the progress of atherosclerotic plaques from a large set of measured data. This system can be modular with option to add and/or modify the rules for better decisions. All outputs must be validated by an experienced sonographer. The second part is to design the artificial neural network based on Error Back-Propagation algorithm. The goal of the network is to compute width of the plaque from B-image using image feature analysis from edge detection. ANN can learn a lot of cases of the plaques using large training set with examples of "good" and "bad" plaques. Well-learned neural network should be a useful tool to fast and reliable decisions depending on the width of the plaque. This long-range research is at the beginning. Design of the expert system is relatively fast; the rules are determined by a sonographer and will be adaptable in the future. Design of the neural network is time-consuming due to complexity of image analysis of ultrasound B-images, i.e. selection of suitable architecture and features for computing of the width of the plaque. This research is a challenge for a large team of experts how to create a helpful software to early diagnostics of the atherosclerosis from measured data and from ultrasound B-images.

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