Texture classification by neural net in medical sonography

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Abstract

We have developed a simple neural net classifier to evaluate textural informational content in the sonographic medical images. The net is trained on a set of texture patterns from sonographic images of testes. The samples in the set were classified by the supervisor into two classes: "normal" and "tumor". After the training the performance was 85% correctly classified images. We are in the stage of collecting data for the independent test set of samples.

1 Introduction

The main purpose of medical sonography is, of course, to establish the patient diagnosis. In this paper we investigate the role of textural information for the diagnostics decision making process.

The analysis of texture[1] in medical images differs a lot from many other laboratory methods used in medicine: the findings cannot be represented by a single number. The texture has to be characterized by a feature vector. However, the evaluation of, say, ten parameter vector is certainly too a complex problem for a human being.

We decided to perform the evaluation process by the computer, to get a sort of yes/no result by the machine. We do not suggest to take the machine decision literally. The machine findings are to be considered as a piece of data presented in a very compressed form. We used the neural network approach. A simple neural net was trained to classify texture feature vectors into two yes/no classes.

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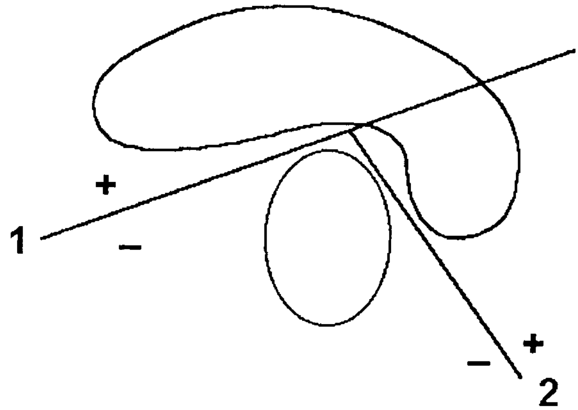

Figure 1: A simple STEPNET classifier

2 The data collection

We have studied texture samples from a collection of ultrasonic images of testes consisting of two classes. The first one were images from patients with normal testes, the second one from patients with tumor. The images were digitized to 256×256 256-grey-level pixels. The texture samples were taken from 16×16 pixel windows. We have collected 187 texture samples: 47 was taken from tumor regions, the other 140 samples were taken from the normal regions. It appears that that the texture features depend on the distance from the probe[2]. Therefore we also included the distance h of the texture window from the probe to be one element of the texture feature vector. The other elements were the Harlick contrast parameters $C_{k,l}$ defined as

$$C_{k,l} = \sum_i \sum_j (i-j)^2 g_{k,l;i,j}$$

where $g_{k,l;i,j}$ are the probabilities to find in the given texture window two pixels separated by k columns and l rows and having greylevels i a j. We used the following 12–component feature vectors

$$(C_{0,2}, C_{2,0}, C_{0,3}, C_{3,0}, C_{3,3}, C_{1,1}, C_{1,2}, C_{2,1}, C_{1,3}, C_{3,1}, C_{2,3}, h)$$

3 The neural net

The feature vectors were input to the STEPNET kind of network[3]. The STEPNET network contains explicit logical gates "and", "or". Its main advantage is that it is adaptively build in the process of training. The main idea as demonstrated in Fig.1.

The STEPNET training is an iterative process. In the first step it attempts to separate the classes using just a single neuron. If the separation after the first step is not perfect further neurons are added to the network. For example in Fig.1 on the "+" side of the separating hyperplane of the first neuron the separation is perfect. On the "−" side there are still examples of both classes. Therefore a second neuron is added operating only within the "−" side of the first neuron separating the remaining examples. The additional neurons operate only in subspaces of the whole configuration space.

For the training purposes we divided the complete data collection into two subsets: the training set (87 samples) and the validation set (100 samples). It appeared that the training was saturated at the level of three neurons. For the optimal net we observed the following performance on the validation set. Out of complete set of 100 samples 87 were correctly classified. Frome these 100 samples there were 23 "tumor" samples: two of them were misclassified by the network as "normal".

4 Conclusions

We do not have for the moment enough statistics to test the performance on the independent testing set. The results for the validation set are certainly better then we have expected and suggest that the textural information might really have a diagnostic value. We stress again that our approach was intentionally extremalistic. In real life nobody would dare to base the diagnosis on an isolated piece of information like the texture feature vector. Getting no-nonsense results for very crude approach is perhaps suggesting that the information on texture might be significant for the diagnosis.

Our conclusion is that the subject is worth of further study. We are going to use the presented model in our ultrasonic laboratory to collect additional data for the independent test set of samples and experimentally use the classifier in parallel to the standard routines to evaluate its performance in a non-formal intuitive way as well.

References

[1] A. Rosenfeld, A. C. Kak, *Digital Picture Processing*, Academic Press, New York (1982).

[2] D.T.Morris, *Ultrasound in Medicine and Biology*, **14**, 387 (1988).

[3] S.Knerr, L.Personnaz, G.Dreyfus, in *Neurocomputing, Algorithms, Architectures and Applications*, NATO ASI Series, eds. F.Fogelman, J.Herault, Springer (1990).