A Use of a Neural Network to Evaluate Contrast Enhancement Curves in Breast Magnetic Resonance Images

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For the diagnosis of breast cancer using magnetic resonance imaging (MRI), one of the most important parameters is the analysis of contrast enhancement. A three-dimensional MR sequence is applied before and five times after bolus injection of paramagnetic contrast medium (Gd-DTPA). The dynamics of absorption are described by a time/intensity enhancement curve, which reports the mean intensity of the MR signal in a small region of interest (ROI) for about 8 minutes after contrast injection. The aim of our study was to use an artificial neural network to automatically classify the enhancement curves as "benign" or "malignant." We used a classic feed-forward back-propagation neural network, with three layers: five input nodes, two hidden nodes, and one output node. The network has been trained with 26 pathologic curves (10 invasive carcinoma [K], two carcinoma-in-situ [DCIS], and 14 benign lesion [B]). The trained network has been tested with 58 curves (36 K, one DCIS, 21 B). The network was able to correctly identify the test curves with a sensitivity of 76% and a specificity of 90%. For comparison, the same set of curves was analyzed separately by two radiologists (a breast MR expert and a resident radiologist). The first correctly interpreted the curves with a sensitivity of 76% and a specificity of 90%, while the second scored 59% for sensitivity and 90% for specificity. These results demonstrate that a trained neural network recognizes the pathologic curves at least as well as an expert radiologist. This algorithm can help the radiologist attain rapid and affordable screening of a large number of ROIs. A complete automatic computer-aided diagnosis support system should find a number of potentially interesting ROIs and automatically analyze the enhancement curves for each ROI by neural networks, reporting to the radiologist only the potentially pathologic ROIs for a more accurate, manual, repeated evaluation.

CONTRAST ENHANCEMENT magnetic resonance imaging (MRI) is an image technique for the study of breast disease. Its performance provides some information not only about tumor existence and extension, but even about its characteristic, allowing the interpretor to distinguish between benign and malignant lesions.

The dynamic study consists of the acquisition of six series of MR images, before and five times after bolus injection of paramagnetic contrast medium (Gd-DTPA). The enhancement of the malignant tissue is faster and more intense than that of the other tissues, probably due to the neoplastic angiogenesis.

The dynamic of absorption in a selected region of interest (ROI) is described by an enhancement curve that plots mean signal intensity (I_{ms}) on the Y-axis and time on the X-axis. The morphology of the curves aids radiologic differential diagnosis between benign lesions and carcinomas.[1,2]

The aim of this work is to present a tool based on an artificial neural network to aid in the classification of enhancement curves with a confidence comparable to that of an expert radiologist, and which would learn by examples.[3,4]

MATERIALS AND METHODS

Imaging

MR was performed with a 1T unit (Impact Expert, Siemens Medical System, Erlangen, Germany). A group of 74 selected patients was examined with bilateral breast coil with axial or coronal three-dimensional spoiled gradient echo (GRE) sequence (pulse repetition time [TR] = 14, echo delay [TE] = 7, flip angle [FA] = 25°), applied before and five times after bolus injection of paramagnetic contrast medium (Gd-DTPA), at 80-second intervals. The slice thickness was less than 3 mm without a gap. After image subtraction, 84 circular ROIs were manually set over the regions with higher contrast enhancement. For each ROI, the pathologic diagnosis was available.

Neural Networks

A three-layer feed-forward neural network[5] was built to classify the enhancement curves. Each curve was represented by six values, acquired respectively with a mean sequence delay of 1 minute 20 seconds after contrast injection. Using the six values, five angular coefficients were obtained, which were sent to the input nodes of the neural network. The network was trained to classify each curve in two groups: benign (B), and malignant lesions (K). The network had one output node that classifies each curve.

The network had one hidden layer. The number of hidden nodes is dynamically adapted (maximum, five nodes) by the Apolloni-Ronchini algorithm.[6] An example of network topology is shown in Fig 1.

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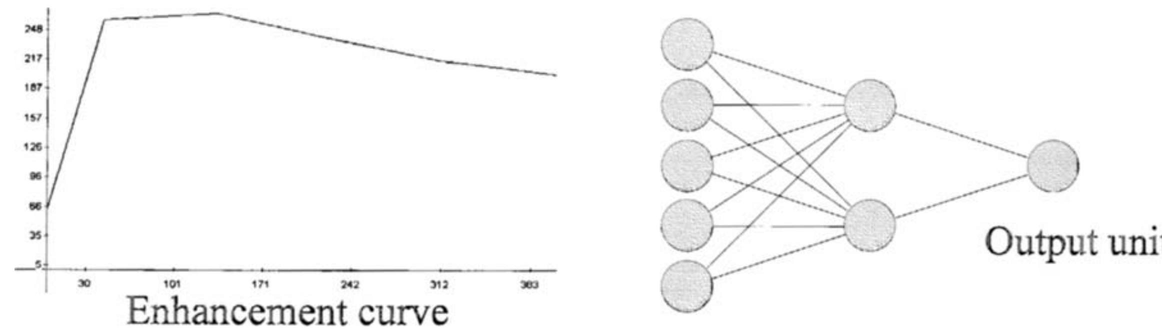

Fig 1. **Neural network topology. Using the six values of signal increment, five angular coefficients are obtained, which are sent to the input nodes of the neural network. Information is free-forwarded through the network until the output unit. The value of output unit is associated with the class of the curves.**

The 84 enhancement curves available were divided into two sets: a training set (26 curves: 10 K, two carcinoma-in-situ [DCIS], and 14 B), and a validation set (58 curves: 36 K, one DCIS, and 21 B). The network was trained using the training set.

Correct classification was attained for 88% of the training set and 76% of the validation set. The best results were achieved with two or three hidden nodes.

RESULTS

The trained network was tested on 58 cases (the validation set). The results are described in Table 1: the network correctly classified 47 curves. For comparison, the same set of curves was analyzed by two radiologists (a breast MR expert and a resident). The expert correctly classified 47 curves; the junior radiologist, 41 curves. Sensitivity and specificity were the same for the network and the senior radiologist (sensitivity, 76%; specificity, 90%), and a little lower for the junior radiologist (sensitivity, 59%; specificity, 90%).

During the training step, the neural network reached an optimal configuration with three nodes in the hidden layer.

Table 1. Results for Validation Set of Neural Network Versus Junior and Senior Radiologist

	Neural Network	Senior Radiologist	Junior Radiologist
True-negative	19	19	19
True-positive	28	28	22
False-negative	9	9	15
False-positive	2	2	2
Sensitivity	76%	76%	59%
Specificity	90%	90%	90%

CONCLUSIONS

These results show that a trained neural network can recognize the pathologic curves at least as well as an expert radiologist. Due to the training procedure, the performances reached by the network are optimized for the available data set. It is interesting that the performance can be comparated with an "intelligent" expert radiologist. The percentage of error of the network is intrinsic to the biologic variability of the enhancement curves.

This algorithm can help the radiologist to attain rapid and affordable screening of a large number of ROIs. A complete automatic computer-aided diagnosis support system should find a number of potentially interesting ROIs, and automatically analyze the enhancement curves for each ROI by neural networks, reporting to the radiologist only the potentially pathologic ROIs for a more accurate, manual, repeated evaluation.

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