Fine Grained Neural Network Classification of Positron Emission Tomography Scans of Alzheimer's and Normal Subjects

Samir Sayegh[+], Satoshi Minoshima[*], David Kuhl[*]
[+]Departments of Physics, Ophthalmology and Center for Ultrafast Optical Science
[*]Department of Internal Medicine, Division of Nuclear Medicine
University of Michigan

Introduction

Positron Emission Tomography (PET) combined with a neural network for discrimination has shown promise for distinguishing patients with Alzheimer's disease (AD) from normal patients (Kippnehahn et al, 1992; Kippenhahn et al., 1994, Chan et al. 1994, Page et al. 1996). Usually only a few parameters from the PET image are used, typically regions of interest (ROI) data based on regional cerebral metabolic rates for glucose (rCMRglc) in multiple lobes. Such representation is highly compressed. Averaging or compression may eliminate a good deal of useful information. Advantages of such compact representation include convenience of usage of standard parameters, intuitive anatomical interpretation and fast training of the neural network. An alternative approach is to use the image as the network input pattern.

A standard backpropagation network (BP) (Le Cun 1985; Rumelhart et al. 1986) is then used to train the neural network. A "hidden layer" operates the "compression" and implicit representation choice. The last layer of weights operates the discrimination between normal and AD classes. Thus the intuition and bias of the human operator are eliminated and lossy compression is avoided.

Backpropagation yields a local optimum solution in weight space. The network is then examined as to its performance on both known ("memorization") and unknown (generalization) scans.

Materials and Methods

Twenty two normal and thirty seven probable AD scans were used for this study. An initial reduction brought the number of pixels for each scan to 1376. Because of different fields of view at acquisition, there were 1019 pixels common to all scans. The number of hidden units for the network was optimized. A single node was used as the output with +1 representing a prediction of normal and -1 representing AD.

In addition to the "memorization" task, the 59 scans were split in training and testing sets in 6 different overlapping experiments in order to test generalization. In each experiment nearly two thirds of normals and two thirds of AD scans were used for training the network and the remaining used for testing.

Relative operating characteristics analysis was performed and the area under the curve used as the figure of merit. This area is equal to the probability of a correct response in a two-alternative forced choice test where a classifier presented with one sample of each (here normal or AD) is forced to determine which sample corresponds to which class.

In a final step the network was tested with a data set (n = 40) consisting of a simulated clinical dementia population including Alzheimer's, Lewy body variant of AD, cerebrovascular disease, depression, normal pressure hydrocephalus and elderly normal controls. The network was *not* trained with the corresponding spectrum of dementia classes.

Results

Training with all 59 scans resulted in 100% correct classification. This clearly demonstrates the viability of the approach and the ability of an appropriately designed network to discriminate normal PET scans from AD scans.

On training and testing with distinct data sets, ROC figures were consistently above .95 with an average value of .97.

On the new data set of simulated dementia population the sensitivity and specificity in distinguishing AD and related diseases from non-AD disorders were 95% (1 false negative) and 63% (7 false positives), respectively, with no inconclusive case. False positives were observed most often in cerebrovascular disease (5 out of 7).

Discussion

Neural Networks have shown success in a variety of classification tasks including PET (Kippenhahn, 1992). Preprocessing of the data plays an important role in achieving correct efficient classification.

Our results on the validation set compare favorably to those of Kippenhahn and al. whose neural networks area under ROC were .85 compared to our > .95. The corresponding figure of merit for the human reader reported by that group was .89.

As stated in Kippenhahn and al, three factors need be considered in a PET-based classification system: the intrinsic diagnostic power of PET, the quality of the image analysis and the classification method (Kippenhahn et al. 1994). The present use of pixel information for neural network input improves the image analysis and is likely to benefit the overall power of PET based system. Our favorable results may be a reflection of this fact.

Results of the simulated dementia population indicate that a high sensitivity can be achieved without training with all classes. The inclusion of other disorders in the training phase can only improve the specificity of the classification.

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