# 2D Analysis of FSE Prostate images using Principal Component Analysis Hybrid Neural Network

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## Introduction

Magnetic resonance (MR) imaging is currently unable to reliably differentiate prostatic adenocarcinoma from benign prostatic hypertrophy (BPH) due to an overlap in the appearance of these two pathologies on different MR sequences (1; 2).

Dynamic contrast-enhanced MR imaging (DCE-MRI) (3; 4) has already been used to aid differentiation, as in general, malignant tissue exhibits more rapid enhancement than benign disease.

Previous work carried out within our centre has attempted to classify normal, benign and malignant disease within the prostate by neural network analysis of the DCE-MRI. The resultant neural network predicted the biopsy result with an accuracy of 89%.

Neural networks are split into 2 main categories; namely supervised & unsupervised. In supervised learning the neural network is provided with the desired response for a particular example. The unsupervised neural network does not require the desired response but determines itself what properties exist and learns to reflect these properties in its output. This has successfully been used for segmentation of brain tissues using different weighted MR images (5).

For this study we have analysed conventional 2D MR images using neural networks in order to determine the classification accuracy.

## Methods

### MR technique

MR imaging was performed on 5 patients using a 1.5 T Signa Advantage (General Electric Medical Systems, Milwaukee) using a pelvic phased array coil for signal reception. Initial localising images were acquired in the sagittal plane to ensure correct positioning of the pelvic phased array coil. A series of axial T2 weighted Fast Spin Echo (FSE) images (TR/TE = 12750/130 ms, 20 cm field of view) with a slice thickness of 2.5cm, matrix of 256*192 were acquired from the apex to the base of the prostate (see Image 1).

### Region of Interest Determination

Regions of interest were acquired using an 8*8 pixel window to sample various anatomical areas of the images. Nine different ROI's from each of the BPH, normal peripheral zone and tumour site were acquired using an 8*8 pixel window.

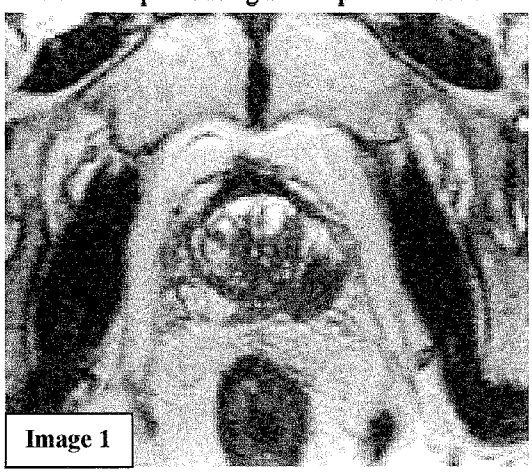

Image 1

### Neural network technique

A square region of interest comprising 64 pixels was used to sample the images. This was then input to the neural network as 64 inputs. A combination of unsupervised and supervised networks was used when a 2D region of interest was presented to the neural network. The initial unsupervised layer projects the 2D data into a space of smaller dimensions thus providing a compressed representation of the original data whilst preserving maximum detail. This information is then passed to a back-propagation network, which acts as a classifier, determining whether the ROI comes from tumour, normal peripheral zone, or BPH.

In order to minimise any bias the data was randomly segmented into 3 parts, 70% for training, 20% for testing, and a final 10% for validation purposes. A cross-validation technique was employed where the neural network architecture was trained 10 times using randomly assigned different training, testing, and validation sets to provide a final average predictive accuracy. The number of misclassifications was then compared to the original classification for that sample.

## Results

The training of the neural network was rapid, taking 2-3 minutes per experiment on a Pentium 2 IBM PC. Once trained the actual classification of the region was under a second. The neural network achieved an accuracy of 89% in classifying normal peripheral zone and accuracies of 78% and 81% for BPH and tumour respectively.

## Conclusions

The use of 2D image analysis can provide the radiologist with a rapid method for analysis. The speed of the neural network in classification, once trained, means that this can be achieved in near real-time conditions.

This technique can be used in combination with the analysis of the DCE-MRI using neural networks where we hope results should improve further.

## References

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