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Image recognition and neuronal networks: intelligent systems for the improvement of imaging information

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Summary

Intelligent computerised systems can provide useful assistance to the physician in the rapid identification of tissue abnormalities and accurate diagnosis in real-time. This paper reviews basic issues in medical imaging and neural network-based systems for medical image interpretation. In the framework of intelligent systems, a simple scheme that has been implemented is presented as an example of the use of intelligent systems to discriminate between normal and cancerous regions in colonoscopic images. Preliminary results indicate that this scheme is capable of high accuracy detection of abnormalities within the image. It can also be successfully applied to different types of images, to detect abnormalities that belong to different cancer types.

Keywords

minimally-invasive imaging procedures, medical image processing, interpretation, textural descriptors, artificial neural networks, intelligent systems in medicine

Introduction

Intelligent systems, particularly those for medical imaging, can be very helpful in medical diagnosis. In most cases, the development of these systems leads to valuable diagnostic tools that may assist physicians in the identification of tumours, or malignancies, by non-invasive or minimally-invasive imaging procedures (e.g. CT, ultrasonography, endoscopy, confocal microscopy, computed radiography and MRI). The aim of such systems is to improve the expert's ability to identify abnormal (e.g. cancerous) regions in tissue, while decreasing the need for aggressive intervention and enhancing the capability to establish an accurate diagnosis. Furthermore, with these techniques it is possible to examine a large area, studying living tissue *in vivo*, possibly at a distance [1]; thus the shortcomings of biopsies, such as discomfort for the patient, delay in diagnosis and limited number of tissue samples, are minimised. In this context, the potentials of new imaging principles, such as fluorescence imaging, or laser-scanning microscopy, are very high.

The main clinical idea behind these developments is early detection of malignant lesions, particularly in stages where local endoscopic therapy is possible. The need for more effective methods of early detection, such as those using intelligent systems for medical imaging, is obvious. Although advanced technical developments in this field are in progress and seem very promising, clinical results are still pending, and more research is indispensable to promote the technologies in question and clarify their real potential for clinical use.

With the increasing importance of computer technology for the healthcare environment, the use of

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computerised intelligent systems can provide useful aids to assist the physician in many cases, eliminate issues associated with human fatigue and habituation, provide rapid identification of abnormalities and enable diagnosis in real-time [2–12].

We describe the state-of-the-art of image recognition and artificial neural networks, in view of their use in intelligent systems. We focus on the use of textural information for characterising medical images and briefly present some models of neuronal networks, discussing their application in medical image interpretation. Experimental results are also reported.

Textural information for the detection of abnormalities

Texture plays an important role in the characterisation of regions in digital images. It carries information about the micro-structure of regions and the distribution of grey levels. A scheme for the recognition of regions based on textural information should be capable of encoding the properties of the texture using a number of parameters, called descriptors. These descriptors are usually represented by sets of statistical measures, thus defining the vectors to be used for recognition; they can be very useful for medical diagnosis.

Our approach has two major processing stages. The first consists of all the processing procedures that will be performed on an image to extract the identifiable features, which will form the feature vectors (Figure 1). The information is entirely dependent on what can be extracted from the original image. To this end, one usually chooses a family of texture attributes that correspond to the components of the feature vectors and account for the main spatial relations between the grey levels of the texture. The texture models underlying these attributes belong to one of three categories: structural, statistical and random process. In the first case, i.e. the structural process, a texture is characterised by a family of primitives and the way in which they are spatially organised (e.g. Gabor filters) [13]. The second category, i.e. the statistical process, involves the use of statistical tools and inference: grey-level co-occurrence matrices [14,15], grey-level run length statistics [16,17], grey-level difference [18] and second-order moments [19]. In the third category, corresponding to random process, textured images are considered as realisations, or samples of spatial random fields. Texture features are extracted by fitting random fields to image data. This encloses auto-binomial Markov fields modelling [20], autoregressive Gaussian models and the Gaussian Markov models [21–24].

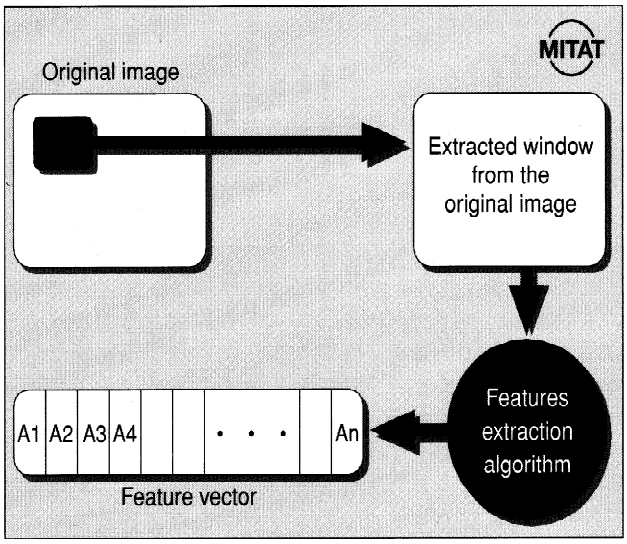

Figure 1. Typical procedure for extracting textural information.

The second processing stage incorporates into one body the information obtained from the first stage, together with background and other information, such as temporal data, relationships between features, etc., in order to draw inferences. This process can be considered analogous to an expert who would consolidate all the facts and verify the truth of the initial hypotheses.

Artificial neural networks for recognising abnormalities in texture regions

Scientific interest in models of neuronal networks or artificial neural networks mainly arises from their potential ability to perform interesting computational tasks. Nodes, or artificial neurons, in neuronal network models are usually considered as simplified models of biological neurons, i.e. living nerve cells, and the connection weights between nodes resemble synapses between neurons [25]. In fact, artificial neurons are much simpler than biological neurons. But, for the time being, it is far from clear how much of this simplicity is justified because, as yet, we have only poor understanding of neuronal functions in complex biological networks.

Artificial neural networks (ANNs) provide an alternative algorithmic model, which is biologically motivated, to computing: the computation is massively distributed and parallel and learning replaces *a priori* program development, i.e. ANNs develop their functionality based on training (sampled)

data. In the framework of medical imaging, advances in ANNs may contribute to the design and development of new computational tools to analyse multidimensional and multimodal medical images. This also holds true in the case of images obtained through minimally-invasive imaging procedures, especially when therapy is guided by these images (video-surgery, interventional radiology, guided radiotherapy, etc.).

In medical imaging, ANNs learning from datasets encounter several difficulties because these sets are usually characterised by incompleteness (missing parameter values), incorrectness (systematic or random noise in the data), sparseness (few and/or non-representable records available from the patient) and inexactness (inappropriate selection of parameters for the given task). In principle, ANNs are able to handle these datasets and are mostly used for their pattern-matching capabilities and their human-like characteristics (generalisation, robustness to noise), in order to assist medical decision making [7,10]. Furthermore, it is acknowledged that ANNs contribute to the improvement of imaging information and to the development and spread of intelligent systems in medical imaging [2,3–6,8,9,11,12,26,27]. ANN-based intelligent systems strongly depend on the existence of technology that provides computers with high computing performance for processing large amounts of information in reasonable time.

The most popular ANN model is the 'multi-layer perceptron' (MLP). In an MLP, whose l-th layer contains N_l nodes, (l = 1,...,M), artificial neurons operate according to the following equations:

$$net_j^l = \sum_{i=1}^{N_{l-1}} w_{ij}^{l-1,l}\, y_i^{l-1}$$

$$y_j^l = f(net_j^l)$$

where net_j^l is, for the j-th neuron in the l-th layer (j = 1,..., N_l), the sum of its weighted inputs. The weights for connections from the i-th neuron at the ($l-1$) layer to the j-th neuron at the l-th layer are denoted by $w_{ij}^{l-1,l}$, y_j^l is the output of the j-th neuron that belongs to the l-th layer, and the logistic function $f(\text{net}_j^l) = (1+\exp(-\text{net}_j^l))^{-1}$ is the j-th's neuron non-linear activation function.

Training an MLP to recognise abnormalities in image regions is typically realised by adjusting the network weights through a minimisation method following an error correction strategy [28]. In an MLP this operation corresponds to minimising the network's learning error:

$$E = \frac{1}{2}\sum_{p=1}^{P}\sum_{j=1}^{N_M}\left(y_{j,p}^M - t_{j,p}\right)^2$$

where $(y_{j,p}^M - t_{j,p})^2$ is the squared difference between the actual output value at the j-th output layer neuron, for an input sample p, and the target output value; p is an index over input–output patterns.

A variety of approaches adapted from numerical analysis have been applied to this special minimisation problem. For example, consider a family of training algorithms that adjust the weights according to the following iterative scheme:

$$w^{k+1} = w^k + \eta\varphi^k \qquad k = 0,1,2,\ldots$$

Note that in this iterative scheme the weights of an MLP are expressed in a simplified form using vector notation. Thus, w^k defines the current weight vector, φ^k is a correction term and η is the learning rate at the kth iteration. Various choices of the correction term φ^k give rise to distinct training algorithms, which are usually classified as first- or second-order algorithms, depending on the derivative-related information they use to generate the correction term. Thus, first-order algorithms are based on the first derivative of the learning error with respect to the weights, while second-order algorithms on the second derivative (see Ref. 29 for a review on first- and second-order training algorithms).

A broad class of first-order algorithms, which are considered much simpler to implement than second-order methods, uses the correction term $\varphi^k = -\nabla E(w^k)$ The term $\nabla E(w^k)$ defines the gradient vector of the MLP and is obtained by means of back-propagation of the error through the layers of the network [30]. The most popular algorithm of this class, 'batch back-propagation' (BP) [30], uses a constant, heuristically chosen, learning rate η that usually takes values in the interval (0, 1). Values in this interval are considered small enough to ensure the convergence of the BP training algorithm and, consequently, the success of learning. However, it is well known that this practice tends to be inefficient [29,30] and the use of adaptive learning-rate strategies is suggested in order to accelerate the learning process (see Refs 29 and 31 for reviews on adaptive learning rate algorithms).

In the experiments described in the next section, an enhanced adaptive learning-rate training algorithm has been employed, called back-propagation with variable step-size (BPVS) [32]. The BPVS algorithm uses a closed formula to calculate the learning rate

based on a local estimation of the Lipschitz constant [32]:

$$\Lambda^k = \frac{\| \nabla E(w^k) - \nabla E(w^{k-1}) \|}{\| w^k - w^{k-1} \|}$$

Then, the weights are updated according to the relation:

$$w^{k+1} = w^k - \frac{1}{2\Lambda^k} \nabla E(w^k)$$

Note that the term $1/2\Lambda^k$ defines the adaptive learning rate for the kth iteration.

After training, the MLP is able to discriminate between normal and abnormal texture regions by forming hyperplane decision boundaries in the pattern space.

Experiments

In the experiments reported, normal/abnormal tissue sample discrimination is based upon the analysis of the grey-level co-occurrence matrices [14,15]. This method evaluates a series of matrices that describe the spatial variation of grey-level values within a local area. In our experiments, this method was implemented by means of four co-occurrence matrices that were computed for each sample area, with a displacement of one pixel and angles of 0, 45, 90 and 135 degrees. Precisely, the following four features were computed on each matrix to produce a 16-dimensional feature vector describing each tissue sample:

- Energy — angular second moment

$$f_1 = \sum_i \sum_j p(i,j)^2$$

- Correlation $f_2 = \dfrac{\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} (i*j)\, p(i,j) - \mu_{xx}\, \mu_y}{\sigma_x\, \sigma_y}$

- Inverse difference moment

$$f_3 = \sum_i \sum_j \frac{1}{1+(i-j)} p(i,j)$$

- Entropy $f_4 = -\sum_i \sum_j p(i,j) \log(p(i,j))$

In the above features, (i,j) corresponds to the (i,j)th entry of the matrices and represents the probability of going from one pixel with grey level (i) to another with a grey level (j) under a predefined distance and angle. In our simulations, these four statistical measures provided high discrimination accuracy that was only marginally increased by adding more measures in the feature vector. A similar compression situation arises in clinical practice: experts in interpreting colonoscopic images usually utilise only a few 'important' features for inference.

An MLP architecture with 16 input neurons, 21 hidden neurons and two output neurons was used for detecting two different types of abnormalities in colonoscopic images taken from two different colons

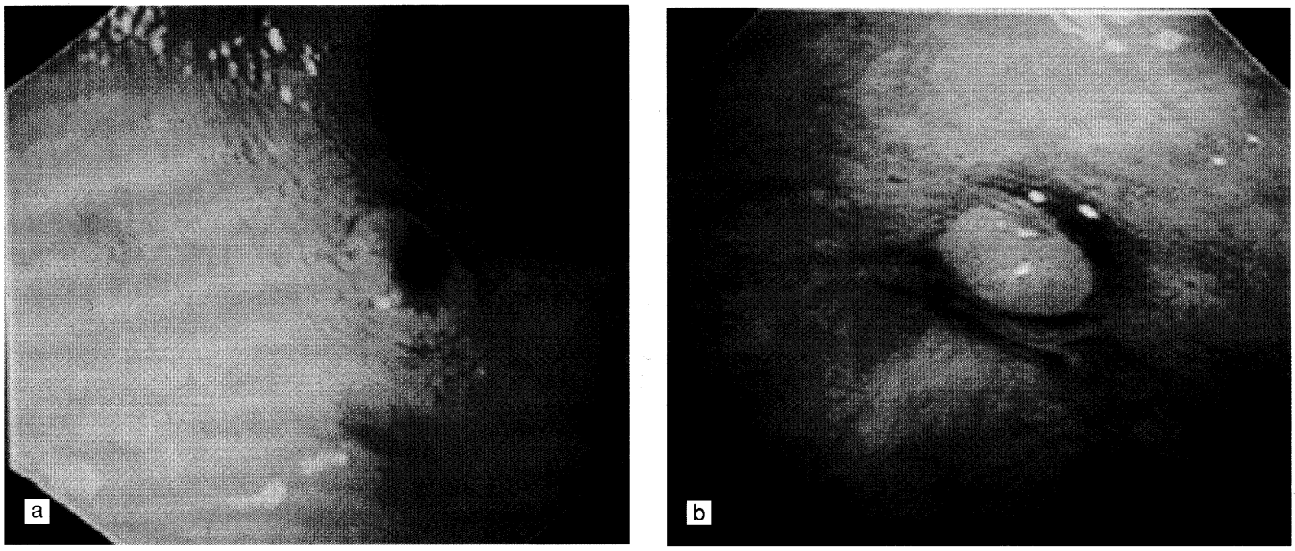

Figure 2. Colonoscopic images used in the experiment: **(a)** Image 1 and **(b)** Image 2.

(for technical details see 6). Image 1 (Figure 2a) is macroscopically a Type IIIs lesion according to Reference 33. Histologically, it is a low-grade cancer. Image 2 (Figure 2b) is macroscopically a Type V lesion according to Reference 33. Histologically, it is a moderately-differentiated carcinoma. Textures from 10 normal and 10 abnormal tissue samples were randomly chosen from each image and used for training the MLP. The performance of the trained MLP was tested on a new set of 80 texture samples (40 normal and 40 abnormal) randomly obtained from the two images.

The experimental MLP exhibited a success rate of 95% in the testing phase (i.e. it misclassified four out of the 80 test samples) and was trained after 103 weight adjustments. But in medical image interpretation the overall accuracy of the ANN alone is not a sufficient measure of its performance [11]. Thus, in Table 1 we complete documentation of performance by presenting the capability of the proposed scheme to assign appropriate characterisations (normal–cancer) to explored-image regions.

It is worth noticing that when discriminating amongst normal and cancer regions in endoscopic images, misinterpreting a cancer region as normal (false negative), which in our case occurs in 2.5% of cases, is more critical than misinterpreting a normal region as cancerous (false positive), which was 7.5%. As shown in Table 1, our scheme exhibits a 92.5% success rate in detecting normal regions in the image and a 97.5% success rate in detecting cancerous regions.

In general, the preliminary results obtained indicate that this scheme is capable of detecting abnormalities within the same image and different types of abnormalities in different images with high accuracy.

Discussion

In this paper we have concentrated on describing issues related to the development and use of artificial neural network-based intelligent systems for medical-image interpretation. Research in intelligent systems to-date remains centred on technological issues and is mostly application-driven. However, previous research and experience suggest that the successful implementation of computerised systems (see Refs 34 and 35), and decision support-systems in particular [36], in healthcare relies on the successful integration of technology with the organisational and social context within which it is applied. Therefore, the successful implementation of intelligent medical-image interpretation systems should not only rely on their technical feasibility and effectiveness, but also on organisational and social aspects that may rise from their applications, as clinical information is acquired, processed, used and exchanged between professionals. All these issues are critical in healthcare applications because they ultimately reflect on the quality of care provided.

Table 1. Percentage classification of MLP's performance in characterising image regions

		System's characterisation %	
		Normal	Cancer
Physician's characterisation	Normal	92.5	7.5
	Cancer	2.5	97.5

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