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 for rapid identification of tissue abnormalities and accurate diagnosis in real time. The paper reviews basic issues on medical imaging and neural network-based systems for medical image interpretation. In the framework of intelligent systems, a simple scheme, implemented in practice, is presented as an application example for the use of intelligent systems of the above kind in discriminating between normal and cancerous regions in colonoscopic images. Preliminary results indicate that this scheme is capable of detecting abnormalities within the image with high accuracy. It can be also successfully applied on different types of images to detect abnormalities that belong to different cancer types.

Keywords: Minimally invasive imaging procedures, Medical image processing, Textural descriptors for medical images, Artificial neural networks, Medical image interpretation, Intelligent systems in medicine.

1. Introduction

Intelligent systems, particularly those for medical imaging, cover a major application area providing significant assistance in medical diagnosis. In most cases, the development of these systems leads to valuable diagnostic tools that may largely assist physicians in the identification of tumours or malignant formations by means of non-invasive or minimally invasive imaging procedures (e.g., computed

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tomography, ultrasonography, endoscopy, confocal microscopy, computed radiography, and magnetic resonance imaging).

The aim of the above 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 make accurate diagnosis. Furthermore, with these techniques it is possible to examine a larger area, studying living tissue *in vivo*, possibly at a distance [1], and thus minimise the shortcomings of biopsies, such as discomfort for the patient, delay in diagnosis, and limited number of tissue samples. In this context, the potentials of new imaging principles, such as fluorescence imaging or laser scanning microscopy, are very high.

The main clinical idea being behind these developments is early detection of malignant lesions, particularly in stages were 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, however, as yet, clinical results are still pending and ongoing and upgraded research is indispensable to promote the technologies in question and clarify their real potential for clinical use.

In conclusion, in times where the healthcare environment is becoming more and more reliant on computer technology, the use of 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] [3] [4] [5] [6] [7] [8] [9] [10] [11] [12].

In what follows, we shall present the state of the art on the subjects of image recognition and artificial neural networks in view of their applications in intelligent systems. In Section 2 we focus on the use of textural information for characterising medical images and in Section 3 we briefly present some models of neuronal networks and discuss their application in medical image interpretation. Next, in Section 4 some experimental results are reported and the paper ends in Section 5 with a short discussion.

2. Textural information for abnormalities detection

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

The approach followed has two major processing stages. The first stage consists of all the processing procedures that will be performed on an image to extract all the identifiable features which will form the feature vectors (see Figure 1). The information is purely 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 which underlie 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 this by the way according to 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: gray-level co-occurrence matrices [14] [15], grey-level run length statistics [16] [17], grey-level difference [18], 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] [22] [23] [24].

The second processing stage decides how to incorporate in one body the information obtained from the first stage together with background and prior information, such as temporal data, relationships about 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.

3. Artificial neural networks for recognising abnormalities in texture regions

Scientific interest in neural network models or *artificial neural networks* mainly arises from their potential ability to perform interesting computational tasks. Nodes, or *artificial neurons*, in neural network models are usually considered as simplified models of biological neurons, i.e. real nerve cells, and the connection weights between nodes resemble to 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 biological networks.

Artificial neural networks (ANNs) provide to computing an alternative algorithmic basis, which is biologically motivated: the computation is massively distributed and parallel and the 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 holds also 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 data sets encounters several difficulties, since these sets may be 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 data sets 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] [4] [5] [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 amount of information in reasonable time.

The most popular ANN is the so-called multi-layer feed-forward neural network (MFNN). In a MFNN, whose l-th layer contains N_l neurons, (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 $f(net_j^l) = (1 + \exp(-net_j^l))^{-1}$ is the j-th's neuron non-linear activation function.

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

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

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

4. Experiments

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

1) Energy - Angular Second Moment $$f_1 = \sum_i \sum_j p(i,j)^2$$

2) Correlation $$f_2 = \frac{\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} (i * j)\, p(i,j) - m_x m_y}{s_x s_y}$$

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

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

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.

A MFNN architecture with 16 input neurons, 21 hidden neurons and 2 output neurons has been used for detecting two different types of abnormalities in colonoscopic images taken from two different colons (for technical details see [6]). Image 1 (Figure 2, left) is macroscopically a Type-IIIs lesion according to [29]. Histologically it is a *low grade cancer*. Image 2 (Figure 2, right) is macroscopically a Type-V lesion according to [29]. Histologically it is a *moderately differentiated carcinoma*. Textures from 10 normal and 10 abnormal tissue samples have been randomly chosen from each image and used for training the MFNN. The performance of the trained MFNNs has been tested on a new set of 80 texture samples (40 normal and 40 abnormal) randomly obtained from the two images.

The experimented MFNN exhibited a success percentage of 95% in the testing phase (i.e. it misclassified 4 out of the 80 test samples) and was trained after 103 weight adjustments. Nevertheless, in medical image interpretation, only the overall accuracy of the neural network 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 is 2.5%, is more critical than misinterpreting a normal region as cancerous (false positive), which in our case is 7.5%. As seen from Table 1, our scheme exhibits a 92.5% of success in detecting normal regions in the image and a 97.5% of success in detecting cancerous regions.

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

5. 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 suggests that the successful implementation of computerised systems (e.g., [30] [31]), and decision support systems in particular (e.g., [32]), in the area of healthcare relies on the successful integration of the 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.

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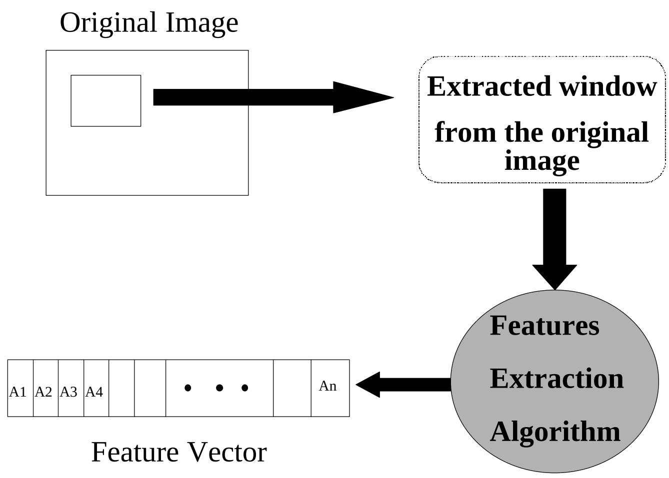
Original Image
Extracted window from the original image
Features Extraction Algorithm
A1
A2
A3
A4
An
Feature Vector

Figure 1.

 

Figure 2.

Figure Legends

Figure 1. Typical procedure for extracting textural information.

Figure 2. Colonoscopic images used in the experiment: “Image1” (left) and “Image 2” (right).

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

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