Computer-aided diagnosis in clinical endoscopy using neuro-fuzzy systems.

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Abstract – **In this paper, an innovative detection system to support medical diagnosis and detection of abnormal lesions by processing endoscopic images is presented. The images used in this study have been obtained using the new M2A Swallowable Imaging Capsule - a patented, video colour-imaging disposable capsule. Schemes have been developed to extract new texture features from the texture spectra in the chromatic and achromatic domains for a selected region of interest from each colour component histogram of endoscopic images. The implementation of an advanced fuzzy inference neural network which combines fuzzy systems and artificial neural networks and the concept of fusion of multiple classifiers dedicated to specific feature parameters have been also adopted in this paper. The detection accuracy of the proposed system has reached to 100%, providing thus an indication that such intelligent schemes could be used as a supplementary diagnostic tool in endoscopy.**

I. INTRODUCTION

Medical diagnosis is based on information obtained from various sources, such as results of clinical examinations and histological findings, patients' history and other data that physician considers in order to reach a final diagnostic decision. Imaging techniques have been extensively used, in the last decades, as a valuable tool in the hands of an expert for a more accurate judgement of patients' condition. In addition, approaches using medical images for automatic detection of lesions have been proposed [1]. Such methodologies can increase expert's identification ability while decreasing the need for aggressive intervention. Moreover, the shortcomings of biopsies, such as discomfort for the patient, delay in diagnosis and limited number of tissue samples can be also minimised. In endoscopic sessions the physicians uses video sequences in order to locate "abnormal" lesions. A system capable to classify image regions to normal or abnormal will act as a second – more detailed- "eye" by processing the endoscopic video. Its exceptional value and contribution in supporting the medical diagnosis procedure is high.

Krishnan, *et al.*[2] have been using endoscopic images to define features of the normal and the abnormal colon. New approaches for the characterisation of colon based on a set of quantitative parameters, extracted by the fuzzy processing of colon images, have been used for assisting the colonoscopist in the assessment of the status of patients and were used as inputs to a rule-based decision strategy to find out whether the colon's lumen belongs to either an abnormal or normal category. The quantitative characteristics of the colon are: mean and standard deviation of RGB, perimeter, enclosed boundary area, form factor, and center of mass. The analysis of the extracted quantitative parameters was performed using three different neural networks selected for classification of the colon. The three networks include a two-layer perceptron trained with the delta rule, a multilayer perceptron with Backpropagation learning and a self-organizing network. A comparative study of the three methods was also performed and it was observed that the self-organizing network is more appropriate for the classification of colon status.

A method of detecting the possible presence of abnormalities during the endoscopy of the lower gastro-intestinal system using curvature measures has been also proposed [3]. In that method, image contours corresponding to haustra creases in the colon are extracted and the curvature of each contour is computed after nonparametric smoothing. Zero-crossings of the curvature along the contour are then detected. The presence of abnormalities is identified when there is a contour segment between two zero-crossings having the opposite curvature signs to those of the two neighbouring contour segments. That proposed method can detect the possible presence of abnormalities such as polyps and tumours.

Endoscopic images contain rich information of texture. Therefore, the additional texture information can provide better results for the image analysis than approaches using merely intensity information. Such information has been used in CoLD (colorectal lesions detector) an innovative detection system to support colorectal cancer diagnosis and detection of pre-cancerous polyps, by processing endoscopy images or video frame sequences acquired during colonoscopy [4]. It utilised second-order statistical features that were calculated on the wavelet transformation of each image to discriminate amongst regions of normal or abnormal tissue. A neural network based on the classic backpropagation learning scheme performed the classification of the features. CoLD integrated the feature extraction and classification algorithms under a graphical user interface, which allowed both novice and expert users to utilise

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effectively all system's functions. The detection accuracy of the proposed system has been estimated to be more than 95%. Recently a new wireless endoscopy system has been developed by Israeli-based Given Imaging Limited and produces high-quality images of the small bowel without pain or discomfort to the patient. The system consists of a small swallow-able capsule containing a battery, a camera on a chip, a light source, and a transmitter. The camera-capsule has a one centimetre section and a length of three centimetres so it can be swallowed with some effort. In 24 hours, the capsule is crossing the patient's alimentary canal.

For the purpose of this research work, endoscopic images have been acquired from human volunteers using this innovative endoscopic device. They have spatial resolution of 171x151 pixels, a brightness resolution of 256 levels per colour plane (8bits), and consisted of three colour planes (red, green and blue) for a total of 24 bits per pixel. The proposed methodology in this paper is considered in two phases. The first implements the extraction of image features while in the second phase a neuro-fuzzy scheme is employed to perform the diagnostic task. The definition and extraction of quantitative parameters from endoscopic images based on texture information is been proposed. This information is finally represented by a set of descriptive statistical features calculated on the histogram of the original image. In this paper, a clustering algorithm is applied for the sample data in order to organise feature vectors into clusters such that points within a cluster are closer to each other than vectors belonging to different clusters. The fuzzy rule base then is created, using results obtained from this algorithm. For the diagnostic part, the concept of multiple-classifier scheme has been adopted, where the fusion of the individual outputs was realised using fuzzy integral.

II. IMAGE FEATURES EXTRACTION

A major component in analysing images involves data reduction which is accomplished by intelligently modifying the image from the lowest level of pixel data into higher level representations. From these higher level representations we can gather useful information; a process called feature extraction. Texture analysis is one of the most important features used in image processing and pattern recognition. It can give information about the arrangement and spatial properties of fundamental image elements. Texture can be described by its colour primitives and their spatial layout. It gives information about the arrangement and spatial properties of fundamental image elements. The goal is to classify objects having irregular texture organisation; the spatial organisation of these texture primitives is, in the worst case, random. For this reason, we focused our attention on nine statistical measures (standard deviation, variance, skew, kurtosis, entropy, energy, inverse difference moment, contrast, and covariance) [5].

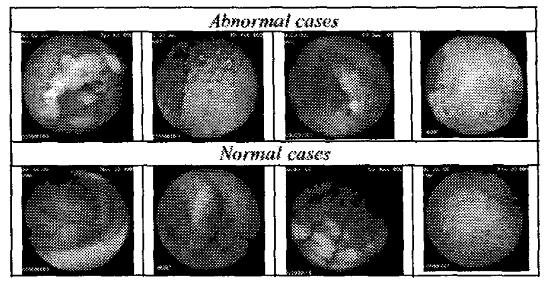

Fig. 1. Selected endoscopic images of normal and abnormal cases

The above statistical measures are estimated on histograms of the original image (1^{st} order statistics).

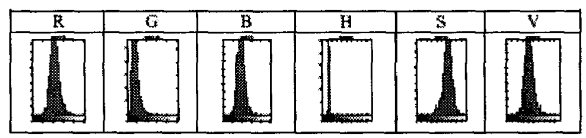

Fig. 2. Histograms in R-G-B-H-S-V planes

The majority of the research has focused on methods applied to grey-level images, where only the luminance of the input signal is utilised. Endoscopic images however contain rich texture and colour information. A method for describing the chromatic aspects of textures is proposed, for feature extraction.

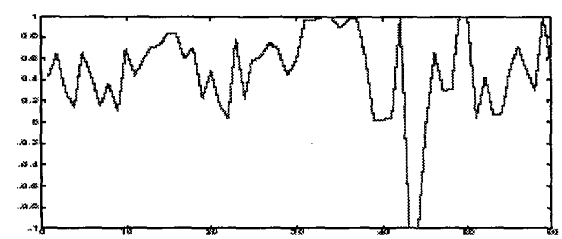

Fig. 3. Statistical Features

All texture descriptors are estimated for all planes in both RGB and HSV spaces, creating a feature vector for each descriptor $D_i=(R_i,G_i,B_i,H_i,S_i,V_i)$. Thus, a total of 54 features (9 statistical measures x 6 image planes) are then estimated. For our experiments, we have used 38 endoscopic images related to abnormal cases and 33 images related to normal ones. Fig. 1 shows samples of selected images acquired using the M2A capsule of normal and abnormal cases. Features based on texture are defined and extracted from those images for diagnosis of their status. Fig. 2 illustrates the histogram feature extraction process for one sample image. The image is analysed into six planes (R,G,B,H,S,V) and their corresponding histograms [6]. The nine statistical measures are estimated in each of these six histograms, therefore their feature values (9x6) are plotted in Fig. 3.

III. Features Evaluation

Recently, the concept of combining multiple classifiers has been actively exploited for developing highly reliable "diagnostic" systems [7]. One of the key issues of this approach is how to combine the results of the various systems to give the best estimate of the optimal result. A straightforward approach is to decompose the problem into manageable ones for several different sub-systems and combine them via a gating network. The presumption is that each classifier/sub-system is "an expert" in some local area of the feature space. The sub-systems are local in the sense that the weights in one "expert" are decoupled from the weights in other sub-networks. In this study, six subsystems have been developed, and each of them was associated with the six planes specified in the feature extraction process (*i.e.* R, G, B, H, S, & V). Each subsystem was modelled with a novel neural network. This provides a degree of certainty for each classification based on the statistics for each plane. The outputs of each of these networks must then be combined to produce a total output for the system as a whole as can be seen in Fig. 4.

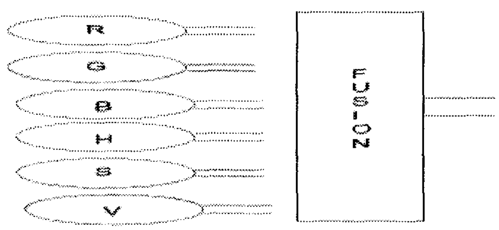

Fig. 4. Proposed fusion scheme

While a usual scheme chooses one best subsystem from amongst the set of candidate subsystems based on a winner-takes-all strategy, the current proposed approach runs all multiple subsystems with an appropriate collective decision strategy. The aim in this study is to incorporate information from each plane/space so that decisions are based on the whole input space. The adopted in this paper methodology was to use the fuzzy integral concept which claims to resolve such issues by combining evidence of a classification with the systems expectation of the importance of that evidence.

A. Clustering Algorithm

The clustering algorithm we apply in this paper consists of two stages. In the first stage the method similar to LVQ algorithm generates crisp *c*-partitions of the data set. The number of clusters c and the cluster centres v_i, $i=1,\dots,c$, obtained from this stage are used by FCM (Fuzzy *c*-means) algorithm in the second stage. The first stage clustering algorithm determines the number of clusters by dividing the learning data into these crisp clusters and calculates the cluster centres which are the initial values of the fuzzy cluster centres derived the second stage algorithm. Let $Z=[z_1,\dots,z_n] \in \mathrm{R}^{np}$ be a learning data. The first cluster is created starting with the first data vector from **Z** and the initial value of the cluster centre is taking as a value of this data vector. Then other data vectors are included into the cluster but only these ones which satisfy the following condition

$$\|z_k - v_i\| < D \tag{1}$$

where $z_k \in Z$, $k=1,\dots,n$ and v_i, $i=1,\dots,c$ are cluster centres, $V=[v_1,\dots,v_n] \in \mathrm{R}^{cp}$, the constant value D is fixed at the beginning of the algorithm. Cluster centres v_i are modified for each cluster (i.e., $i=1,\dots,c$) according to the following equation

$$v_i(t+1) = v_i(t) + a_t(z_k - v_i(t)) \tag{2}$$

where $t = 0,1,2,\dots$ denotes the number of iterations, $a_t \in [0,1]$ is the learning rate and it is decreasing during performance of the algorithm (depending on the number of elements in the cluster). As a result of performance of this algorithm we get the number of clusters c, we have divided data set into the clusters, and we know values of cluster centres v_i $i=1,\dots,c$ which we can use as initial values for the second stage clustering algorithm. In the second stage the fuzzy c-means algorithm has been used. FCM is a constrained optimisation procedure which minimises the weighted within-groups sum of squared errors objective functions J_m with respect to fuzzy membership's u_{ik} cluster centres v_i, given training data z_k, $i=1,\dots,c$; $k=1,\dots,n$

$$\min_{(U,V)}\{J_m(U,V;Z) = \sum_{k=1}^{n}\sum_{i=1}^{c}(u_{ik})^m \|z_k - v_i\|^2\} \tag{3}$$

The number of clusters c and the initial values of cluster centres v_i come from the first stage clustering algorithm.

B. Fuzzy Inference Neural Networks

The two-stages clustering algorithm provides the fuzzy *c*-partition of the sample data. The number of rules in the proposed fuzzy inference neural network (FINN) equals to the number of clusters c obtained from the clustering algorithm. The proposed FINN scheme is a MIMO adaptive fuzzy logic system with centre average as defuzzification concept. The schematic of the FINN scheme which is shown in Fig. 5 consists of four layers. The first two layers L1 and L2 correspond to IF part of fuzzy rules whereas layers L3 and L4 contain information about THEN part of these rules, and perform the defuzzification task. There are $c \times q$ elements in layer L1. They realise the membership functions which are defined by

$$\mu_j^i = \exp\left[-\left(\frac{x_j - v_{ij}}{\sigma_{ij}}\right)^2\right] \tag{4}$$

for $j = 1,...,q$ and $i = 1,...,c$. The values v_{ij} in Eq. (4) denote the centres of the Gaussian membership functions and are equal to the values of the vectors v_i which have been derived from the second stage clustering algorithm. The value σ_{ij} defines the widths of the Gaussian membership functions. These values have been estimated according to

$$\sigma_{ij} = \left(\sum_{k=1}^{n} u_{ik}(z_{kj} - v_{ij})^2 \Big/ \sum_{k=1}^{n} u_{ik} \right)^{1/2} \tag{5}$$

These values are calculated based on the matrix **U** which elements represent fuzzy memberships of z_k i^{th} cluster and have values obtained from the second stage clustering algorithm.

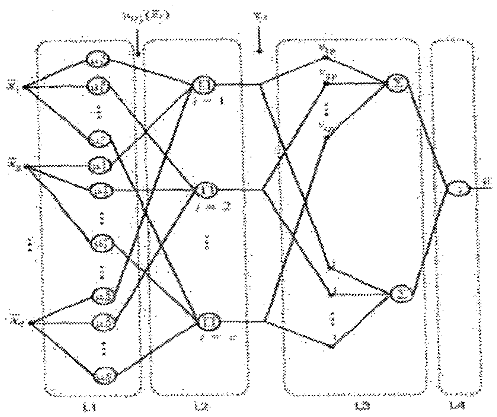

Fig. 5. Schematic of IFNN structure

The second layer L2 has c elements which realise multiplication operation because of using Larsen rule in fuzzy reasoning procedure. Each element in this layer is associated with one fuzzy rule. Outputs of this layer represent the fire strength of the rules, expressed by

$$\tau_i = \prod_{j=1}^{q} \mu_j^i(\overline{x}_j) \tag{6}$$

Layer L3 contains the parameters v_{ip}, for $i = 1,...,c$. The only one element in layer L4 performs division operation. Layers L3 and L4 serve as the center average defuzzifier.

$$\overline{y} = \sum_{i=1}^{c} v_{ip}\tau_i \Big/ \sum_{i=1}^{c} \tau_i \tag{7}$$

The multi-layer connectionist structures of FINN scheme allow us to apply, learning procedures similar to the back-propagation method which is commonly used as learning algorithm for feed-forward multi-layer artificial neural networks [8]. Based on the idea of the back-propagation the following updates for tuning the parameters of Gaussian membership functions have been derived

$$v_{ip}(t+1) = v_{ip}(t) - \eta(\overline{y} - \hat{y}) \frac{\prod_{j=1}^{q} \exp\left[-\left(\frac{\overline{x}_j - v_{ij}}{\sigma_{ij}}\right)^2\right]}{\sum_{i=1}^{c}\prod_{j=1}^{q} \exp\left[-\left(\frac{\overline{x}_j - v_{ij}}{\sigma_{ij}}\right)^2\right]} \tag{8}$$

$$v_{ij}(t+1) = v_{ij}(t) - \beta \frac{(\overline{x}_j - v_{ij})(v_{ip} - \overline{y})}{(\sigma_{ij})^2} (\overline{y} - \hat{y}) \frac{\prod_{h=1}^{q} \exp\left[-\left(\frac{\overline{x}_h - v_{ih}}{\sigma_{ih}}\right)^2\right]}{\sum_{i=1}^{c}\prod_{h=1}^{q} \exp\left[-\left(\frac{\overline{x}_h - v_{ih}}{\sigma_{ih}}\right)^2\right]}$$

$$\sigma_{ij}(t+1) = \sigma_{ij}(t) - \gamma \frac{(\overline{x}_j - v_{ij})^2(v_{ip} - \overline{y})}{(\sigma_{ij})^3} (\overline{y} - \hat{y}) \frac{\prod_{h=1}^{q} \exp\left[-\left(\frac{\overline{x}_h - v_{ih}}{\sigma_{ih}}\right)^2\right]}{\sum_{i=1}^{c}\prod_{h=1}^{q} \exp\left[-\left(\frac{\overline{x}_h - v_{ih}}{\sigma_{ih}}\right)^2\right]}$$

C. *Fuzzy Integral*

Fuzzy integral (FI) is a promising method that incorporates information from each space/plane so that decisions are based on the whole input space in the case of multiple classifier schemes. FI combines evidence of a classification with the systems expectation of the importance of that evidence. By treating the classification results a series of disjointed subsets of the input space Sugeno defined the g_λ-fuzzy measure [9].

$$g(A \cup B) = g(A) + g(B) + \lambda g(A) g(B); \ \lambda \in (-1, \infty) \tag{9}$$

Where the λ measure can be given by solving the following non-linear equation.

$$\lambda + 1 = \prod_{i=1}^{K}\left(1 + \lambda g^i\right) \ \lambda > -1 \tag{10}$$

The $g^i, i \in \{1,...,K\}$ values are fuzzy densities relating to the reliability of each of the K feature networks and satisfy the conditions of fuzzy sets laid out by Sugeno.

IV. RESULTS

The proposed approach was evaluated using 73 clinically obtained endoscopic M2A images (33 abnormal images and 38 normal images). These images were then split into a training group containing 25 normal images and 23 abnormal. Six sub-networks, each one with 9 inputs and 2 outputs have been constructed. Each of the sub-networks was trained in turn using a threshold value of 0.015 to stop training. The values of the learning coefficients in this iteration process have been set as follows. $\eta = 0.3$, $\beta = 0.01$, $\gamma = 0.02$. The value of the weighting exponent in the second stage clustering algorithm has been chosen as m=1.9.

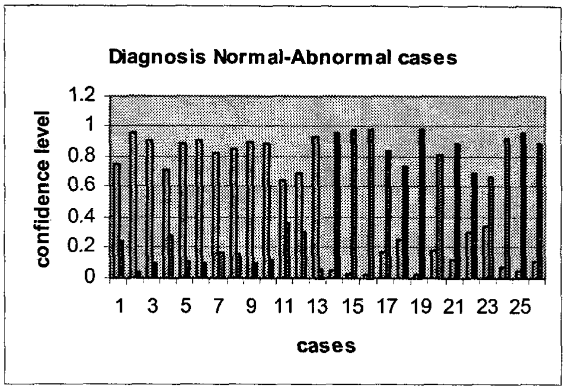

Fig. 6: Performance using FI fusion method.

The resulting fused outputs showed 100% classification with confidence levels ranging from 0.8-1.00. The remaining data were then analysed / tested using each of the space/plane networks and with the results shown in Fig. 6. The confidence levels range from 0.64-0.98 and the accuracy is still 100%. The FI concept has been used here to combine the results from each sub-network.

V. Conclusions

An approach on extracting texture features from endoscopic images using the M2A Given Imaging capsule has been developed. Statistical features based on texture are important features, and were able to distinguish the normal and abnormal status in the selected clinical cases. The multiple classifier approach used in this study with the inclusion of a novel neuro-fuzzy network algorithm provided encouraging results. In this paper we studied two-stages clustering algorithm to determine the number of rules, number of fuzzy sets, and initial values of the parameters (centres and widths) of the fuzzy membership functions. These values have been applied as starting points for learning procedures based on the gradient descent learning algorithm. Future studies will be focused on further development of this "diagnostic" system by incorporating additional features, investigation of algorithms for reduction of input dimensionality as well as the testing of this approach to the IVP-endoscopic capsule which is under development.

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