TUMOR DETECTION IN COLONOSCOPY USING THE UNSUPERVISED k-WINDOWS CLUSTERING ALGORITHM AND NEURAL NETWORKS

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Abstract

This study presents an approach to automatically detect tumors in colonoscopic images that is based on the synergy between unsupervised clustering and artificial neural networks. First the noisy data set is partitioned into clusters and then a different neural network is trained from data of each detected cluster. Each network is therefore considered a "local expert" with regards to patterns of the same cluster as the one used for training. The results from applying this approach in interpreting colonoscopy images are promising, generating networks that were able to detect malignant regions of interest with high accuracy.

1 Introduction

Colon cancer can be prevented and cured if it is detected early. An intelligent environment that would assist physicians to early diagnose colorectal cancer or detect colorectal cancer precursors by providing on–line services such as analysis of imaging data and classification will definitely increase the efficiency of the typical screening methodologies. In technical terms, the problem in automatic image interpretation is to associate sets of pixels (structures) that appear in an image with the unknown objects that are present in the scene from which the image was taken.

During colonoscopy the physician interprets physical surface properties of the tissue, such as the roughness or the smoothness, the regularity, and the shape, to detect abnormalities. This task is particularly difficult. Even within the same colon, one section may have very different characteristics from another. Adjacent surfaces of the colon lining showing different properties are distinguished on the basis of the textural variations of their tissue. These textural alterations of the colonic mucosal surface signify that this property could also be used for the automatic detection of lesions [3, 5, 7].

Automatic detection of lesions in colonoscopy is subject to uncertainties due to inaccurate measurements and the lack of precise models of the image characteristics of lesions. Given a colonoscopy image, the "true" features associated with the physical surface properties of the tissue are not exactly known to the system developer [5]. Usually, one or more feature–extraction models are used to provide values for each feature's parameters [4]. The findings are then used to infer the correct interpretation. On this same task of interpretation on the basis of local changes on the properties of the tissue under examination, the performance of human perception is considered outstanding. Moreover, medical experts have the ability to either add or remove components from an image to give meaning to what they see. Physicians can also adapt to changes to the extent that even a distorted image can be recognized.

In this work, we combine texture segmentation, unsupervised clustering and neural networks for the automatic detection of lesions in colonoscopy images (see Figure 1). The rest of the paper is organized as follows: in the next Section we outline the proposed methodology. In Section 3 we de-

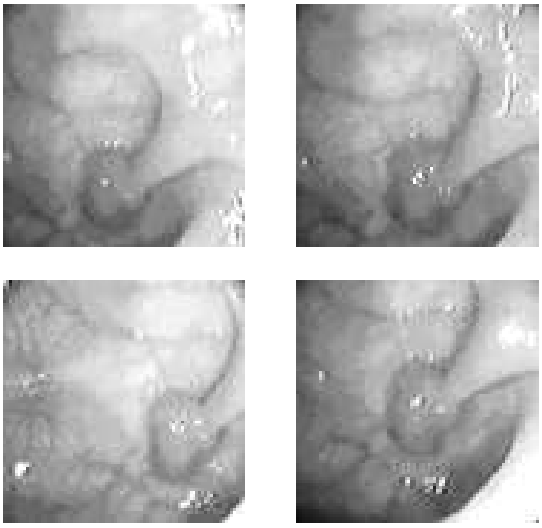

Figure 1: Frames of a video sequence showing a polypoid tumor of the colon

scribe the proposed unsupervised clustering algorithm and in Section 4 we give details on the experiments contacted and present the results. The final Section contains concluding remarks and a short discussion.

2 Proposed Methodology

In this study instead of constructing a global model for the pattern classification, we construct several local models for the different neighborhoods of the feature space. For this task, we use the novel k-windows clustering algorithm [10] to automatically detect neighborhoods with similar characteristics in the feature space. This algorithm, with a slight modification (unsupervised k-windows algorithm), has the ability to endogenously determine the number of clusters present in the dataset during the clustering process. Once, the clustering process has been completed, a trained feedforward neural network acts as the local classifier for each cluster. In synopsis, the proposed methodology consists of the following five steps:

1. Texture segmentation.
2. Identify the clusters present in the training set.
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4. For each cluster, train a different feedforward neural network using training patterns from this cluster solely.
5. Assign the patterns of the test set to the clusters previously detected.
6. Use the trained feedforward networks to obtain the classification scores on the test set.

3 Unsupervised k-windows Clustering Algorithm

Intuitively, the k-windows algorithm [10] tries to place a d-dimensional window containing all patterns that belong to a single cluster; for all clusters present in the dataset. At first, k points are selected. The k initial d-ranges (windows), of size a, have as centers these points. Subsequently, the patterns that lie within each d-range are identified. Next, the mean of the patterns that lie within each d-range (i.e. the mean value of the d-dimensional points) is calculated. The new position of the d-range is such that its center coincides with the previously computed mean value. The last two steps are repeatedly executed as long as the increase in the number of patterns included in the d-range that results from this motion satisfies a stopping criterion. The stopping criterion is expressed by a variability threshold θ_v that corresponds to the least change in the center of a d-range that is acceptable to recenter the d-range. Once movement is terminated, the d-ranges are enlarged in order to capture as many patterns as possible from the cluster. Enlargement takes place at each dimension separately. The d-ranges are enlarged by θ_e/l percent at each dimension, where θ_e is user defined, and l stands for the number of previous successful enlargements. After the enlargement in one dimension is performed, the window is moved, as described above. Once movement terminates, the proportional increase in the number of patterns included in the window is calculated. If this proportion does not exceed the user–defined coverage threshold, θ_c, the enlargement and movement steps are rejected and the position and size of the d-range are reverted to their prior to enlargement values. Otherwise, the new size and position are accepted. If enlargement is accepted for dimension $d' \geqslant 2$, then for all dimensions d'', such that $d'' < d'$, the

enlargement process is performed again assuming as initial position the current position of the window. This process terminates if enlargement in any dimension does not result in a proportional increase in the number of patterns included in the window beyond the threshold θ_c.

The key idea to automatically determine the number of clusters, is to apply the k-windows algorithm using a sufficiently large number of initial windows. The windowing technique of the k-windows algorithm allows for a large number of initial windows to be examined, without a significant overhead in time complexity. Once all movement and enlargement processes for all windows, terminate, all overlapping windows are considered for merging. The merge operation is guided by a merge threshold θ_m. Having identified two overlapping windows, the number of patterns that lie in their intersection is calculated. Next the proportion of this number to the total patterns included in each window is calculated. If the mean of these two proportions exceeds θ_m, then the windows are considered to belong to a single cluster.

4 Experimental Results

The main difficulties in recognizing regions of interest in colonoscopy images are due to resolution change and variable perceptual conditions (shading, shadows, lighting conditions, and reflections) that result in noisy data. In our setting, textures from normal and abnormal tissue samples were randomly chosen from four frames of the same video sequence, which exhibited resolution change, different perceptual direction of the physician, different diffused light conditions, and were used for training and testing.

No filtering or preprocessing of the data was applied. The co–occurrence matrices method has been used for feature extraction. Co–occurrence matrices [1] represent the spatial distribution and the dependence of the gray levels within a local area. More specifically, each colonoscopic image was separated into windows of size 16 by 16 pixels. Then the co-occurrence matrices algorithm was used to gather information regarding each pixel in an image window [3, 5]. In our experiments the feature vectors contained sixteen elements each, and therefore the first layer of the FNNs consisted of sixteen nodes. Thus, FNNs having 16 input nodes, 2 layers of hidden neurons consisting of 8 and 7 neurons respectively and 2 output nodes (198 weights and 17 biases) were trained to discriminate between normal and abnormal image regions using 1200 randomly selected patterns from the video frames. The training procedure stopped when the networks were trained for 300 epochs and subsequently their performance was evaluated on the test sets. This process was repeated 100 times for all the considered training algorithms.

Numerical experiments were performed using a Clustering and a Neural Network C++ Interface built under the Red Hat Linux 7.3 operating system using the GNU compiler collection (gcc) version 3.2. Four neural network training algorithms were implemented and tested, namely: Resilient Back Propagation (RPROP) [9], Improved Resilient Back Propagation (iRPROP) [2], Scaled Conjugate Gradient (SCG) [8], Adaptive On–Line Back Propagation (AOBP) [6]. The performance of the trained FNNs with respect to the accurate pattern classification in the test sets is reported in Table 1. All four algorithms used to train FNNs after the successful clustering are capable of detecting tumor in the colonoscopic images considered with high accuracy.

5 Conclusions

This paper presents an approach for automatic tumor detection in colonoscopic images, which draws from the disciplines of clustering and artificial neural networks. A set of local neural experts is trained on data previously clustered with the unsupervised k-windows algorithm, which has the capability to automatically determine the number of clusters present in a dataset. The trained networks are then used to classify the test patterns. The results of this small scale study of the clustering-neural networks synergy look promising for this challenging task. Further investigation is need in a larger scale to fully explore the benefits and identify limitations of the approach.

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Training Algorithm	Classification (%)			
	mean	σ	*max*	*min*
	Frame 1			
RPROP	94.89	0.48	95.76	94.30
iRPROP	93.11	3.48	95.43	77.52
SCG	91.57	6.20	94.55	59.58
AOBP	91.84	3.07	93.44	76.06
	Frame 2			
RPROP	95.09	0.49	95.96	94.12
iRPROP	93.85	1.16	95.71	91.35
SCG	90.56	8.26	94.48	59.73
AOBP	90.10	8.53	93.65	58.75
	Frame 3			
RPROP	73.26	1.83	76.97	67.67
iRPROP	71.53	2.60	75.58	63.36
SCG	70.95	2.15	76.71	67.27
AOBP	70.83	1.52	75.03	68.07
	Frame 4			
RPROP	74.99	2.74	78.93	65.55
iRPROP	70.97	3.75	78.35	63.29
SCG	68.88	5.37	86.39	57.79
AOBP	74.95	1.48	79.66	71.88

Table 1: Classification results for the algorithms tested

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References

[1] R.M. Haralick. Statistical and structural approaches to texture. *IEEE Proc.*, 67:786–804, 1979.

[2] Christian Igel and Michael Hüsken. Improving the Rprop learning algorithm. In H. Bothe and R. Rojas, editors, *Proceedings of the Second International ICSC Symposium on Neural Computation (NC 2000)*, pages 115–121. ICSC Academic Press, 2000.

[3] S.A. Karkanis, G.D. Magoulas, and N. Theofanous. Image recognition and neuronal networks: Intelligent systems for the improvement of imaging information. *Minimal Invasive Therapy & Allied Technologies*, 9:225–230, 2000.

[4] C.G. Looney. *Pattern recognition using neural networks*. Oxford University Press, Oxford, UK, 1997.

[5] G.D. Magoulas, V.P. Plagianakos, and M.N. Vrahatis. Network-based colonoscopic diagnosis using on-line learning and differential evolution. *Applied Soft Computing, to appear*.

[6] G.D. Magoulas, V.P. Plagianakos, and M.N. Vrahatis. Adaptive stepsize algorithms for on-line training of neural networks. *Nonlinear Analysis, T.M.A.*, 47(5):3425–3430, 2001.

[7] G.D. Magoulas, V.P. Plagianakos, and M.N. Vrahatis. Improved neural network–based interpretation of colonoscopy images through on–line learning and evolution. In *EUNITE 2001 Conference*, Tenerife, Spain, 2001.

[8] M. F. Moller. A scaled conjugate gradient algorithm for fast supervised learning. *Neural Networks*, 6:525–533, 1993.

[9] M. Riedmiller and H. Braun. A direct adaptive method for faster backpropagation learning: The rprop algorithm. In *Proceedings of the IEEE International Conference on Neural Networks, San Francisco, CA*, pages 586–591, 1993.

[10] M.N. Vrahatis, B. Boutsinas, P. Alevizos, and G. Pavlides. The new k-windows algorithm for improving the k-means clustering algorithm. *Journal of Complexity*, 18:375–391, 2002.