

MULTIRESOLUTION COLOUR TEXTURE ANALYSIS FOR CLASSIFYING COLON CANCER IMAGES

J. K. Shuttleworth¹, A. G. Todman¹, R. N. G. Naguib¹, B. M. Newman¹ and M. K. Bennett²

¹Royal Victoria Infirmary, Newcastle upon Tyne, UK

²Biocore, MIS, Coventry University, Coventry, UK.

Abstract – Co-occurrence matrices are commonly used to extract fine texture information from images, and have been found to be a useful tool for measuring dysplasia in histological images of the colon. Pathologists, however, measure dysplasia in tissue samples at structural as well as cytological levels. We present our findings after investigating modifications to the co-occurrence matrix technique to measure this low frequency colour texture information for the classification of colon cancer images.

Keywords – Texture, microscopy, cancer, image analysis, colon

I. INTRODUCTION

As previously discussed in [1], multiple microscope objectives are commonly used by pathologists to assess dysplasia at cytological and histological levels. Dysplasia is evident in the crypts of the lamina propria (low frequency, gross texture) and in the spatial organisation of the component cells (high frequency, fine texture). Co-occurrence matrices [6,7] have been used extensively for fine texture analysis of histological images of this type [2-5] and are a useful statistical method for texture analysis. For most of these applications, co-occurrence matrix texture measurements are extracted with small distances between source and target pixels ($d < 10$ pixels). For the purposes of measuring fine texture in colon section images, this has proved to be a valuable technique [1, 4], but may not be suitable without modification for measuring a more structural exhibition of dysplasia.

II. OBTAINING LOW FREQUENCY TEXTURE MEASUREMENTS

The simplest way to measure this low frequency texture using co-occurrence matrices is to increase d . Fig. 1 shows a tissue sample taken from a dysplastic colon polyp. Fig. 2 shows the regional texture response using the energy metric as described in [6] with $d = 16$ and a window size of 25 extracted from the hue channel of Fig. 1 using methods for increasing rotational invariance as discussed in [1]. Comparing the texture image created with $d=2$ (Fig. 3) with Fig. 2, it is clear that the response to finer details, such as edges, is reduced and the response to larger features, such as areas of differing hue, has increased with larger values of d .

An undesired feature of this approach is the effect of variations in pixel values in regions that, for the purposes of assessing structural abnormalities, would be classed as homogeneous by a human observer. These variations can be seen in Fig. 2 as gaps and rough edges.

The variance caused by fine detail could be removed by reducing the size of the image. This idea is attractive for many reasons: high frequency noise will be lost, smaller values of d can be used and there are fewer valid pixel pairs, making the extraction of the measurements a much less processor intensive task. Fig. 4 shows the energy response of

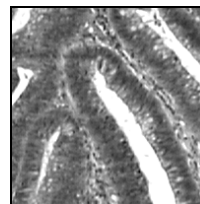


Fig. 1. Example colon section image at $\times 100$ objective

the original image scaled down to 25%. The texture image has been re-scaled to match previous examples. The technique does have disadvantages as well as advantages. While we lose high frequency noise, we also lose some image data: the reduction in the number of valid pixel pairs increases calculation speeds but also gives a less reliable result. In our example of an image scaled to 25%, we are disregarding almost 94% of the available data – a 200×200 pixel image will have roughly 40,000 valid pairs, while a 50×50 image has only 2,500.

To overcome the problems associated with extracting low frequency texture information as described above, we have made use of a variation of the co-occurrence matrix technique that combines the favourable elements of both simple approaches to assess lower frequency texture. By applying colour texture analysis as described in [1] to a Gaussian smoothed image with larger values of d , the technique can operate with large pixel distances without suffering from the effects of pixel variations in regions that we wish to be treated as homogeneous. Fig. 5 shows the energy response of the new technique applied to the hue channel of the original image. Note that regional variations are minimal, while structural features of the original image are clearly visible.

To create the texture image in Fig. 5, the contribution of neighbouring pixels was calculated as a Gaussian function of the distance between each pixel in the neighbourhood at the central pixel, with a neighbourhood defined as the pixels within an 8 pixel radius of the source or target. To improve execution times, this can be implemented simply by convolving the source image with a Gaussian kernel before extracting texture information.

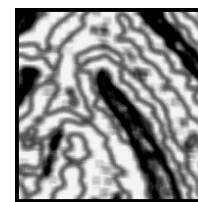
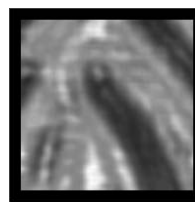


Fig. 2. Energy response with $d=16$

Fig. 3. Energy response with $d=2$

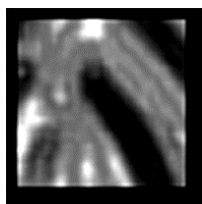
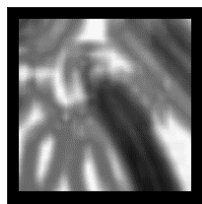


Fig. 4. Scaled energy response

Fig. 5. Energy response using $d=16$ and Gaussian averaging

III. RESULTS

Using a dataset of 175 images classified by an experienced pathologist into normal tissue, dysplastic polyps and tumours, discriminant analysis was used to determine the texture measurements that strongly correlate with classification. Using pair distances of 10, 20, 30, 40, 50 and 60 pixels, extracted from each channel of the RGB and HSB colour models, gave a list of 36 features, 21 of which were selected by discriminant analysis as being correlated with image classification. By combining these features with previously selected features [1] that measure fine texture, it was possible to improve on previous classification accuracy. Table I show accuracy results for fine texture analysis and combined fine and gross texture analysis. All results are cross-validated using a leave one out method and are divided into two sets of statistics: Harsh statistics assume three distinct groups and lenient statistics consider just two groups (normal and abnormal) for comparison with other work in this area.

IV. DISCUSSION

The addition of low resolution texture information has improved overall classification accuracy significantly. Perhaps more importantly, negative predictive value has drastically increased compared to results obtained using only high resolution texture information, making the combined feature set even more useful as part of an automated classification system – the probability of negative classifications being incorrect is greatly reduced. While our previous results show a high level of accuracy, many of the misclassifications were gross misclassifications of cancerous tissue as normal, severely reducing the negative predictive value.

TABLE I
CLASSIFICATION ACCURACY

Harsh

Texture	Accuracy	Sens.	Spec.	PPV	NPV
Fine	96.6%	95.3%	100.0%	100.0%	88.5%
Combined	98.3%	99.2%	95.7%	98.4%	97.8%

Lenient

Texture	Accuracy	Sens.	Spec.	PPV	NPV
Fine	97.1%	96.1%	100.0%	100.0%	90.2%
Combined	99.4%	100.0%	97.8%	99.2%	100.0%

(Sens. = Sensitivity, Spec. = Specificity, PPV = Positive predictive value, NPV = Negative predictive value)

V. CONCLUSION

There are many more challenges to be met before a reliable automated system can be created. Images in this study are small sections of “typical” tissues – very different from the large sections of differentiated tissue that would need to be analysed to aid diagnosis or prognosis in any way.

However, these results are promising and may lead to a reduction in the disparity between features measured by automated techniques and those that human pathologists use to guide classification. There are still many possible parametric variations and modifications that can be made, and further investigation of multi-resolution colour texture analysis for the classification of colon sections may lead to even more accurate results.

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