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An Optical Machine Vision System for Applications in Cytopathology

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An Optical Machine Vision System for Applications in Cytopathology

Jonathan M Blackledge, Fellow, IET and Dmitry A Dubovitskiy, Member, IET

Abstract— **This paper discusses a new approach to the processes of object detection, recognition and classification in a digital image focusing on problem in Cytopathology. A unique self learning procedure is presented in order to incorporate expert knowledge. The classification method is based on the application of a set of features which includes fractal parameters such as the Lacunarity and Fourier dimension. Thus, the approach includes the characterisation of an object in terms of its fractal properties and texture characteristics. The principal issues associated with object recognition are presented which include the basic model and segmentation algorithms. The self-learning procedure for designing a decision making engine using fuzzy logic and membership function theory is also presented and a novel technique for the creation and extraction of information from a membership function considered. The methods discussed and the algorithms developed have a range of applications and in this work, we focus the engineering of a system for automating a Papanicolaou screening test.**

Index Terms— **Computer vision, Segmentation, Object recognition, Contour detection, Edge detection, Decision making, Self-learning, Fuzzy logic, Image morphology, Cytopathology, Cervical smear analysis, Papanicolaou screening test.**

I. Introduction

The cervix is an important site for pathological studies, particularly in women of reproductive age. It protects the uterine cavity from intrusion of pathogenic micro-organisms, promotes the movement of spermatozoa to the ovule and holds a fetus in the uterus at pregnancy. The conventional study of cellular structures on stained glass slides for cytological reporting is a routine procedure for the early detection of pre-carcinoma conditions. Visual inspection allows an estimate to be made of the state of the cervix and a diagnosis to be developed based on the cytological pattern observed providing an adequate specimen is available. Worldwide, approximately 471,000 women are diagnosed with invasive carcinoma of the cervix each year and the order of 233,000 die from the disease. Although mortality from cervical cancer continues to decrease due to improved screening programmes, it remains among the most common female cancers in many countries. For example, in the United Kingdom, it is ranked eleventh for women, sexually transmitted infections by certain strains of the human papilloma virus being the major cause of the condition.

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A. Papanicolaou Screening

Cervical cancer is preceded by a precancerous condition called Cervical Intraepithelial Neoplasia (CIN) which can be easily treated if detected. It is therefore important to identify CINs through a Papanicolaou screening test commonly known as a 'PAP test'. A small sample of cells from the surface of the cervix is removed and smeared onto a glass slide and the material is fixed in alcohol. The slide is then stained and the sample(s) examined under a microscope, a search being carried to detect abnormal cells. Examination typically involves observing the nucleus of a cell and inspecting it for characteristics that point toward abnormalities that include size, texture and colour. For example, if the nucleus is enlarged relative to the area of the cytoplasm as shown in the example given in Figure 1 then there is a likelihood of abnormal activity within the nucleus.

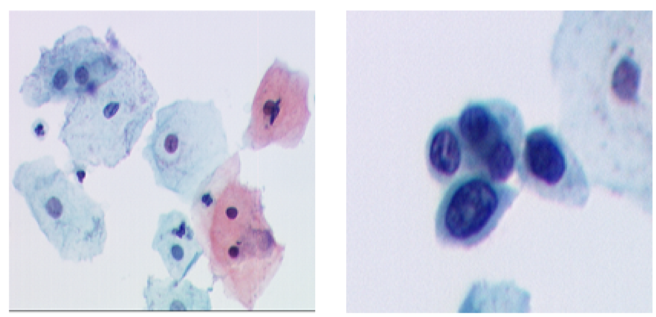

Fig. 1. Example of normal (left) and abnormal cell clusters (right) where, in the latter case, the Cytoplasm to Nuclei area ratio is enlarged.

The order of four million cervical smears are taken annually in the UK and fifty million in USA, for example, and a principal diagnostic problem is that about one fifth of the borderline preparations show the disease at an advanced stage on referral and biopsy. Overall there is a 50% 'failure' rate in detecting significant diseases within borderline cases. In addition there is a 50% 'failure' in detecting significant deceases within negative cases. The reasons for this vary from extraction of a sample, the preparation of the slide, but most of all, from the sequential reading of a slide in the diagnostic laboratory when human error occurs.

In current practices world-wide a diagnosis is performed manually. It typically takes 8-10 minutes for a cytopathologist to screen a slide and involves upto 300 movements of a microscope over the slide. This approach not only takes time but inevitably leads to outcomes in which it is not possible to guarantee consistent and accurate results as many borderline results are generated, for example. It is therefore of significant value if accurate image analysis and object recognition techniques can be developed in an attempt to automate the process and produce a system that provides a reliable, consistent and quantitative estimation of CINs and other abnormalities to improve upon the subjective assessments of a cytopathologist.

A typical screening session involves a cytopathologist analysing a slide under the microscope with a magnification up to 400x. The output is related to the number of slides and working hour per cytologist and an increase in either reduces the speed and reliability of the results. Telecytology [5] provides a large number of digital images for consideration which can lead increased human error. Moreover, in telecytology the cytopatholoist is not usually able to examine cellular details and to change the focal plane of the image. In virtual microscopy a digital image of the entire slide is generated and consequently the image file can become very large $\sim$4-7Gb. Another problem with virtual microscopy is that the focal plane limits the representation of the specimen. Virtual microscopy is used for proficiency tests and there are a number of commercially available medical imaging assistant tools [11], [12], [13]. However, a cytopathologist is still an important factor in the 'diagnostic cycle'. Furthermore, due to compression and/or differences in the focal depth, many images may not provide a clear enough representation of a cell in comparison to those obtained using conventional microscopy. Thus, the development of automated recognition and classification systems provides the potential for introducing quality control in national screening procedures.

B. *Image Analysis and Pattern Recognition*

Conventional microscopy, as applied to cytopathology, involves the use of image processing methods that are often designed in an attempt to provide a machine interpretation of an image, ideally in a form that allows some decision criterion to be applied, such that a pattern and/or object can be recognised [1], [2]. Pattern recognition uses a range of different approaches that are not necessarily based on any one particular theme or unified theoretical approach. The main problem is that, to date, there is no complete theoretical model for simulating the processes that take place when a human interprets an image generated by the eye, i.e. there is no fully compatible model, currently available, for explaining the processes of visual image comprehension. Hence, machine or computer vision remains a rather elusive subject area in which automatic inspection systems are advanced without having a fully operational theoretical framework as a guide. Nevertheless, numerous algorithms for interpreting two- and three-dimensional objects in a digital image have and continue to be researched in order to design systems that can provide reliable automatic object detection and recognition in an independent environment, e.g. [3], [4], [14], [16], [25].

Vision can be thought of as a process of linking parts of the visual field (objects) with stored information or templates about their significance for the observer. There are a number of questions concerning vision such as: (i) what are the goals and constraints? (ii) what type of algorithm or set of algorithms is required to effect vision? (iii) what are the implications for the process given the types of hardware that might be available? (iv) what are the levels of representation required to achieve vision? The levels of representation are dependent on what type of segmentation can and/or should be applied to an image. For example, we may be able to produce a primal sketch from an image via some measure of the intensity changes in a scene which are recorded as place tokens and stored in a database. This allows sets of raw components to be generated, e.g. regions of pixels with similar intensity values or sets of lines obtained by isolating the edges of an image scene and computed by locating regions where there is a significant difference in the intensity. However, such sets are subject to inherent ambiguities when computed from a given input image and associated with those from which an existing database has been constructed. Such ambiguities can only be overcome by the application of high-level rules, based on how humans interpret images, but the nature of this interpretation is not always clear. Nevertheless, parts of an image will tend to have an association if they share size, colour, figural similarity, continuity, shading and texture, for example. For this purpose, we are required to consider how best to segment an image and what form this segmentation should take.

The identification of the edges of an object in an image scene is an important aspect of the human visual system because it provides information on the basic topology of the object from which an interpretative match can be achieved. In other words, the segmentation of an image into a complex of edges is a useful pre-requisite for object identification. However, although many low-level processing methods can be applied for this purpose, the problem is to decide which object boundary each pixel in an image falls within and which high-level constraints are necessary. Thus, in many cases, a principal question is, which comes first, recognition or segmentation?

Compared to image processing, computer vision (which incorporates machine vision) is more than automated image processing. It results in a conclusion, based on a machine performing an inspection of its own. The machine must be programmed to be sensitive to the same aspects of the visual field as humans find meaningful. Segmentation is concerned with the process of dividing an image into meaningful regions or segments. It is used in image analysis to separate features or regions of a pre-determined type from the background; it is the first step in automatic image analysis and pattern recognition. Segmentation is broadly based on one of two properties in an image: (i) similarity; (ii) discontinuity. The first property is used to segment an image into regions which have grey (or colour) levels within a predetermined range. The second property segments the image into regions of discontinuity where there is a more or less abrupt change in the values of the grey (or colour) levels.

In this paper, we consider an approach to object detection in an image that is based on a new segmentation (edge detection) algorithm based on a Contour Tracing Algorithm and space-oriented filter [6]. The image usually requires enhancing before it is process and for this purpose a novel self-adjusting sharpening filter has been developed as discussed in this paper. The segmented object is then analysed in terms metrics derived from both a Euclidean and fractal geometric perspective, the output fields being used to train a fuzzy inference engine and the recognition structure being based on some of the methods reported in [15], for example. The approach considered is generic in that it can, in principle, be applied to any type of imaging modality. There are numerous applications of this technique especially when self-calibration and leaning is mandatory. Example applications may include remote sensing, non-destructive evaluation and testing and many other applications which specifically require the classification of objects that are textural. However, in this paper we focus on one particular application, namely, the diagnosis of cervical cancer based on standard Papanicolaou screening test images.

II. Object Recognition Architecture

Suppose we have an image which is given by a function $f(x, y)$ and contains some object described by a set $S = \{s_1, s_2, ..., s_n\}$. We consider the case when it is necessary to define a sample which is somewhat 'close' to this object. This task can be reduced to the construction of some function determining a degree of proximity of the object to a sample - a template of the object. Recognition is the process of comparing individual features against some pre-established template subject to a set of conditions and tolerances. The process of recognition commonly takes place in four definable stages: (i) image acquisition and filtering (as required for the removal of noise, for example); (ii) object location (which may include edge detection); (iii) measurement of object parameters; (iv) object class estimation. We now consider the common aspects of each step. In particular, we consider details on the design features and their implementation together with their advantages, disadvantages and proposals for a solution whose application, in this paper, focuses on problems in cytopathology.

Image acquisition depends on the technology that is best suited for integration with a particular application. For pattern recognition in cytopathology, for example, high fidelity digital images are required for image analysis whose resolution is, at least, compatible by the image acquisition equipment used for human inspection. For cytopathology this involves optical microscopy and for the application considered in this work, the microscope is equipped with digital camera. The colour images generated, examples of which are presented in this paper are, in general, relatively noise free and are digitised using a standard CCD camera. Nevertheless, it is important that good quality images are obtained that are homogeneous with regard to brightness and contrast, for example. Unless consistently high quality images can be generated that are compatible with the sample images used to design a given computer vision system, then that same system can be severely compromised.

The system discussed in this paper is based on an object detection technique that includes a novel segmentation method and must be adjusted or 'fine tuned' for the each area of application. The necessary features associated with the 'object' must be computed for a particular area of application. In the work reported here, this includes objects for which fractal models are well suited [23], [1], [2]. The system provides an output (i.e. a decision) using a knowledge database and outputs a result by subscribing different objects. The 'expert data' in the application field creates the knowledge database by using a supervised training system with a number of model objects [18]. The recognition process is illustrated in Figure 2, a process that includes the following steps:

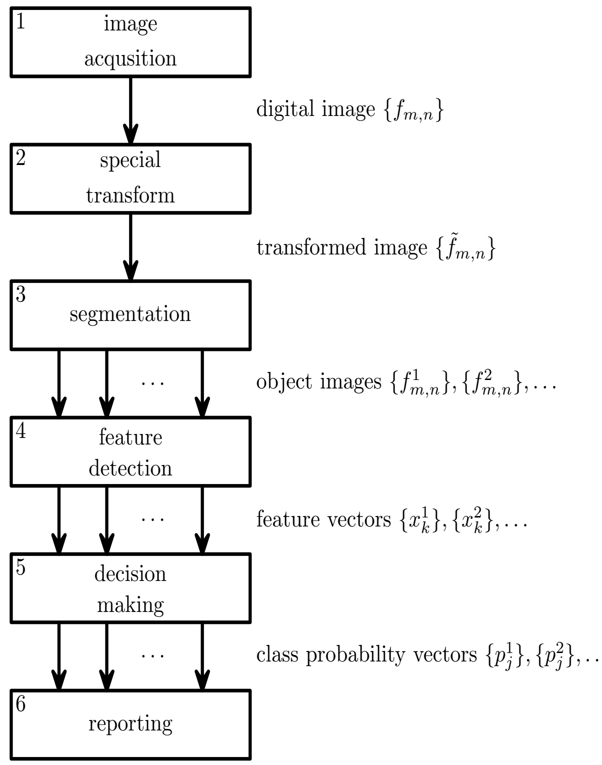

Fig. 2. Recognition processes.

1) Image Acquisition and Filtering
A physical object is digitally imaged and the data transferred to memory using current image acquisition hardware available commercially. The image is filtered to reduce noise and to remove unnecessary features such as light flecks.
2) Special Transform: Edge Detection
The digital image function $f_{m,n}$ is transformed into $\tilde{f}_{m,n}$ to identify regions of interest and provide an input dataset for the segmentation and feature detection operations [17]. This transform avoids the use of edge detection filters which have proved to be highly unreliable in the present application.
3) Segmentation
The image $\{f_{m,n}\}$ is segmented into individual objects $\{f^1_{m,n}\}, \{f^2_{m,n}\}, \ldots$ to perform a separate analysis of each region. This step includes such operations as thresholding, morphological analysis and contour tracing using the convex hull method developed in [6].
4) Feature Detection
Feature vectors $\{x^1_k\}, \{x^2_k\}, \ldots$ are computed from the object images $\{f^1_{m,n}\}, \{f^2_{m,n}\}, \ldots$ and corresponding $\{\tilde{f}^1_{m,n}\}, \{\tilde{f}^2_{m,n}\}, \ldots$. The features are numeric parameters that characterize the object inclusive of its texture.

The feature vectors computed consist of a number of Euclidean and fractal geometric parameters together with statistical measures in both one- and two-dimensions. The one-dimensional features correspond to the border of an object whereas the two-dimensional features relate to the surface within and/or around the object.

5) Decision Making
   This involves assigning a probability to a predefined set of classes [21]. Probability theory and fuzzy logic [19] are applied to estimate the class probability vectors $\{p_j^1\}, \{p_j^2\}, \ldots$ from the object feature vectors $\{x_k^1\}, \{x_k^2\}, \ldots$. A fundamental problem is to establish a quantitative relationship between features and class probabilities, i.e.

$$\{p_j\} \leftrightarrow \{x_k\}$$

   A 'decision' is the estimated class of the object coupled with the a probabilistic accuracy [20].

The application considered in this paper is based on algorithms that have been designed to solve problems associated with the above steps details of which are given in [6] which provides algorithms on threshold selection and a contour tracing algorithm using the 'convex hull' property. However, the application considered here requires some additional algorithms to solve the object recognition problem associated with cytopathology. This is because edge detection is particularly difficult to solve for images consisting of many cells and a special space-oriented filter has therefore been designed to extract parameters associated with the spatial distribution of object borders. This includes a self-adjustable filter for enhanced object sharpness that has been considered as an inter-medium mask filter in order to clarify a cellular border. For characterisation, the line of objects found using the steps described above, need to be considered in terms of their major properties.

With regard to the design of a decision making engine, the approach proposed is based on establishing an expert learning procedure in which a Knowledge Data Base (KDB) is constructed based on answers that an expert makes during a manual mode. Once the KDB has been developed, the system is ready for application in the field and provides results automatically. However, the accuracy and robustness of the output depends critically on the extent and and completeness of the KDB as well as the quality of the input image, primarily in terms of its compatibility with those images that have been used to generate the KDB. The algorithm discussed in Section IV has no analogy with previous contour tracing algorithms and has been designed to trace a contour of an object with any level of complexity to produce an output that consists of a consecutive list of coordinates of an object's edge. The algorithm is optimised in terms of computational efficiency and can be realised in a compact form suitable for hardware implementation.

III. Region of Interest Segmentation

For applications in cytopathology, a fundamental requirement is to select Regions of Interest (ROI) for detail review. The ROI is not taken to be the object itself but its local boundary. This approach improves the efficiency associated with the process of recognition, a process that is recursive and involves different settings required to evaluate the probability of a the presence of a cell in the image. The algorithm used for ROI segmentation is based on adaptive thresholding and morphological analysis. The adaptive image threshold is given by

$$T_x = \frac{1}{2}\left(\min_y \left(\max_x f(x,y)\right) - \langle \max_x f(x,y)\rangle_y\right)$$
$$+\langle \max_x f(x,y)\rangle_y,$$
$$T_y = \frac{1}{2}\left(\min_x \left(\max_y f(x,y)\right) - \langle \max_y f(x,y)\rangle_x\right)$$
$$+\langle \max_y f(x,y)\rangle_x,$$
$$T = \begin{cases} T_x, & T_x \geq T_y, \\ T_y, & \text{otherwise}, \end{cases}$$

where $\langle \cdot \rangle_x$ and $\langle \cdot \rangle_y$ are the means within column x and row y, respectively. This approach provides a solution for extracting the most significant features in the image, in this case, the nucleus of cells. If these objects cover an extensive area of the image, then this 'filter' provides the fastest compact solution. An example of the output generated by this algorithm is shown in Figure 3). In order to obtain a clear boundary, morphological analysis is applied to select objects with a predefined area. This is discussed in the following section.

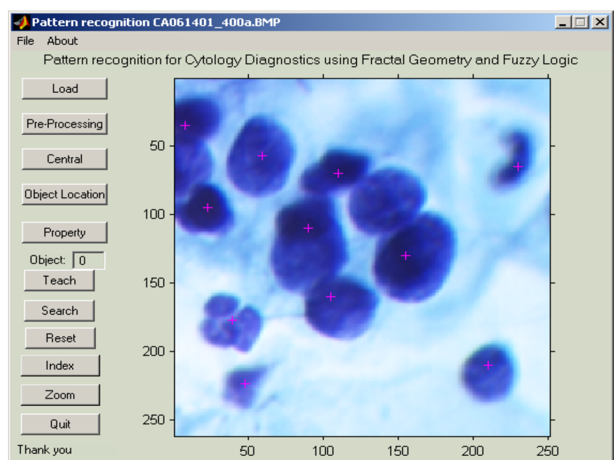

Fig. 3. Example of ROI segmentation where + points to the location in the image where there is a cell.

IV. Space Oriented Filter Design for Edge Detection

Edge detection is used to identify the edges in an image which are those areas that correspond to object boundaries. To find these edges, an algorithm is designed that looks for places in the image where the intensity changes rapidly; this is typically based on using one of two principal criteria:

(i) areas where the first derivative of the intensity is larger in magnitude than some threshold;
(ii) regions where the second derivative of the intensity has a zero crossing.

There are many standard digital filters available for this process. Taking into account that in many images, high frequency noise (white noise) is usually present, we consider an appropriate adaptive filtering strategy.

A. Noise Reduction by Adaptive Wiener Filtering

Edge detection methods typically require an effective noise reduction algorithm in order to eliminate noise which should be undertaken adaptively. A well known adaptive filter is the Wiener filter which can be applied to an image adaptively, tailoring itself to the local image variance. When the variance is large, the Wiener filter performs little smoothing; when the variance is small, it performs more smoothing. This approach often produces better results than linear filtering. The adaptive filter is more selective than a comparable linear filter, preserving edges and other high frequency parts of an image. Although the Wiener filter requires greater computational time than linear filtering, it performs better when the noise is constant-power or 'white' additive noise, such as Gaussian noise which is one of the conditions required to simplify the result of applying a least squares criterion.

The Wiener filter algorithm uses a pixel-wise adaptive filtering procedure with neighborhoods of size m-by-n to estimate the local image mean and standard deviation. It estimates the local mean and variance around each pixel given respectively by

$$\mu = \frac{1}{nm} \sum_{r,c \in \eta} I_s(r,c) \text{ - } \textit{mean of the brightness of the image}$$

and

$$\sigma^2 = \frac{1}{nm} \sum_{r,c \in \eta} \left(I_s^2(r,c) - \mu^2\right) \text{ - } \textit{dispersion}$$

where the sum is taken over the n-by-m local neighborhood of each pixel in the image I. The algorithm then creates a pixel-wise Wiener filter using the following estimates

$$I_D\,(r,c) = \mu + \frac{\sigma^2 - v^2}{\sigma^2}\,(I_s(r,c) - \mu)$$

where ν^2 is the noise variance. If the noise variance is not given, the filter uses the average of all the local estimated variances. In this work, the Wiener filter is used as a first step to processing the image prior to applying a space oriented edge detection filter in order to provide an image that is optimal with regard to solving the edge detection problem for applications in cytopathology. Example results are shown in Figures 4 and 5. Figure 4 shows the original image and Figure 5 is the result of applying the Wiener filter described above.

B. Edge Detection

Edge detection methods are based on a number of derivative estimators. For some of these estimators, it is possible to specify whether the operation should be sensitive to horizontal or vertical edges, or both. In each case, the aim is to return a binary image - an array containing elements which are either 0 or 1 where 1 represents an element of an edge and 0 represents an empty edge space. Moreover, within the context of the overall approach, it is assumed that different edge detectors will yield minimal differences. In this application a Canny filter [8] is used to provide a first estimate of the edge boundaries of a cell nucleus.

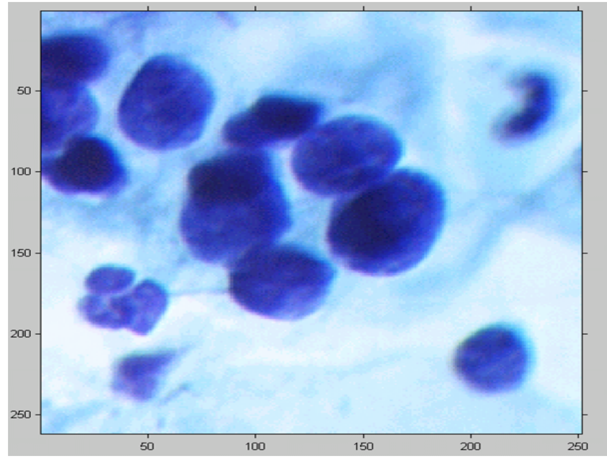

Fig. 4. Original image of a cell cluster obtained from a cervical smear after staining.

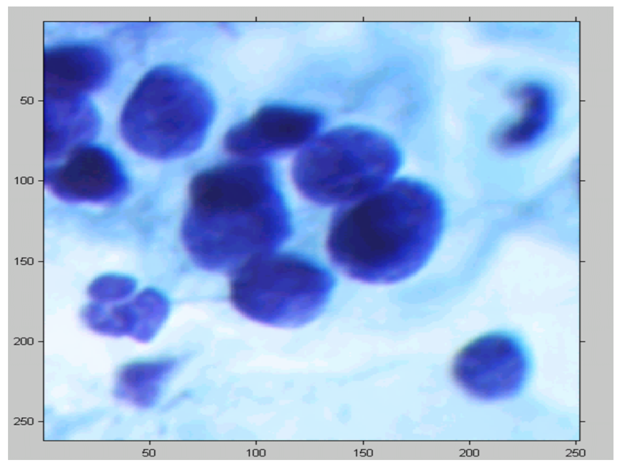

Fig. 5. Adaptive Wiener filtered image.

The Canny edge detector is based on a functional analysis to derive an optimal function for edge detection, starting with three optimisation criteria, namely, good detection, good localization, and only one response per edge under white noise conditions. The 1D 'Canny function' is accurately approximated by the derivative of a Gaussian function which is then combined with a Gaussian of identical standard deviation in the perpendicular direction, truncated at 0.001 of its peak value, and split into suitable masks. Underlying this method, is the idea of locating edges at the local maxima of the gradient magnitudes of a Gaussian-smoothed image. In addition, the Canny implementation employs a hysteresis operation on edge magnitude in order to make edges reasonably connected. Finally, a multiple-scale method is employed to analyse the output of the edge detector.

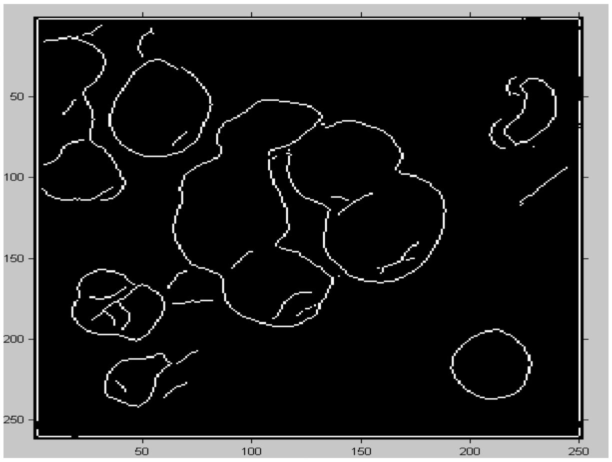

Fig. 6. Application of a Canny Filter to Figure 5.

An example of applying a Canny filter to Figure 5 is given in Figure 6. This result typically illustrates that it is not possible to uniquely tell where the edge of a cell or nuclei occurs, especially when there is a connection between one edge with another gradient, where Canny edge detection introduces errors. For this purpose, it is necessary to design a new filter which is discussed in the following section.

C. Space Oriented Filtering

In some cases, the nuclei of the cells in a cervical smear can appear very close together, or be in touch with a foreign object such as a bacterium. In this case, an extra filter must be used to obtain a contour boundary. For this purpose, a space-oriented filter for the detection of 'holes' has been developed. The nuclei represent a 'hole' if the image is visualised in terms of a surface in which the nuclei are regions of lower intensity. The filter has been designed to take account of the following: (i) objects should be of a quasi-spherical form; (ii) the search space should include objects with lower intensity (i.e. which have a darker colour); (iii) it is necessary to find only the surface of a cell without a hysteresis zone. An example of a profile that is characteristic of a nucleus is given in Figure 7. The same principle can of course be used for other objects.

The solution to this problem is compounded in the algorithm that is now described, the basic procedure being illustrated in Figure 8. To start with, we estimate the brightness of the central area (using a window of 9$\times$9 pixels) and a circle (a layer consisting of 2 pixels). If the center is dark, we suppose that it is part of the nuclei and compare the intensity along the white line in Figure 8 with the central zone. If the profile along this line has a maximum and minimum gradient, we consider the angle between them. If the angle lies in the range 79^o to 248^o degrees then we assume that we are near to the border of a nucleus. This angle can be estimated automatically or established as a constant and 'hard-wired' into the algorithm.

The next step is to apply the hole detection method (red and brown lines in Figure 8). This hole detection algorithm is extended in a procedure to decide whether the area under investigation is a nuclei or otherwise. In Figure 8, the

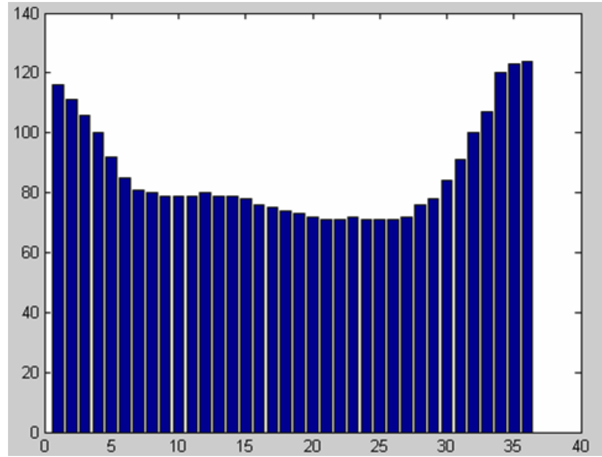

Fig. 7. Example intensity profile of a Nucleus.

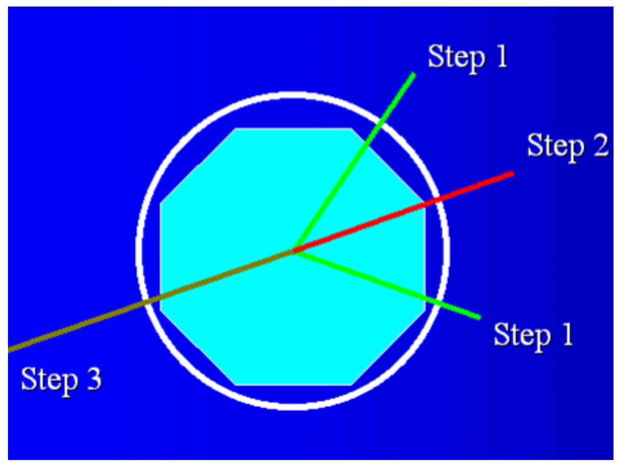

Fig. 8. Mask used for space-oriented filtering.

maximum length of the brown line is approximately 70 pixels (which depends on the image resolution) and can be chosen automatically. A useful procedure is to check the direction toward the center of a nuclei but this is application dependent. If, for a period, there is no hole, then the present position is ignored. If the test for detecting a hole gives a positive result, as in an index figure, the line from the center of a hole up to the border of a hysteresis is drawn.

In the central part of the image (Figure 5) one can see 5 joint kernels in the centre of the image. To automatically find the edges between all of these nuclei requires a special algorithm for object separation The sequence of steps associated with the algorithm designed for this purpose can be divided into following list:

(i) estimation of the edge;
(ii) search the boundaries of the cell;
(iii) calculate the direction to the center of a core;
(iv) search the opposite edge of the core;
(v) calculate the centers of the kernels;
(vi) save the index map of the figure.

Estimation of edge expectation

Pre-processing can be used to form part of the estimated performance for edge expectation. This allows for accelerated scanning of the image. For this purpose a structure estimation operator is applied at the central part of the mask as shown in Figure 8. This selects only those nuclei of interest and avoids spending computer time processing other parts of the image.

Searching the boundaries of the cell (Step 1)

The ring around of the central part of a mask (Figure 8) is decomposed using the operator

$$R = [x_1, x_2, ...x_n]$$

In the following analysis we evaluated the gradient sequence:

$$g_{1..n} = \frac{dR}{dn}$$

Upon demarcation of a core and after the derivation, the gradient window will contain two maxima - positive and negative. The polar angle then gives the direction of the nuclear center θ_1.

Calculation of the direction of the center (Step 2)

In this step, the expected direction to the center is updated by means of a check on the position of the angle on a plane between the maxima obtained in the previous step. In general, for the purpose of recognition, a point on the binary map uses a convolution technique with a series of masks for searching the exact point on the object edge. The sequence of masks used is as follows:

$$M = \left\{ \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 1 & 1 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix}, \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 1 & 1 & 1 \end{bmatrix}, \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}, \begin{bmatrix} 0 & 0 & 0 \\ 1 & 1 & 0 \\ 1 & 1 & 1 \end{bmatrix} \right\}$$

The appropriate mask is applied in the direction of a local gradient rate and gives a maximal convolution between both the points obtained from the previous step. From the definition of the angle θ_2, utilizing the *a priori* results, we form the ratio

$$\theta = \frac{\theta_1 + \theta_2}{2}$$

The logical conformity of the mask and adjacent points of the binary map is further evaluated and the binary representation of object is determined via

$$I_B(r, c) = \begin{cases} 1, & \text{if } M \notin I_g; \\ 0, & \text{if } M \in I_g. \end{cases}$$

The profile information (gradient and amplitude) is memorized for Step 3 (discussed below). The dimension $I_B(r, c)$ corresponds to the dimension and starting map $I_g(r, c)$.

Search for the opposite edge of a core (Step 3)

The opposite gradient is searched for by finding of centre of a nuclei together with the gradient on the opposite end which serves as a final confirmation for the coordinates of object. In Figure 9 these lines are illustrated in brown. The opposite profile has to have the same properties as at Step 2. This prevents any wrong detection through irregularities in the image. If the opposite profile is found, then a green line is 'painted' on the index binary image from the center to the boundary of the nucleus as in Figure 10.

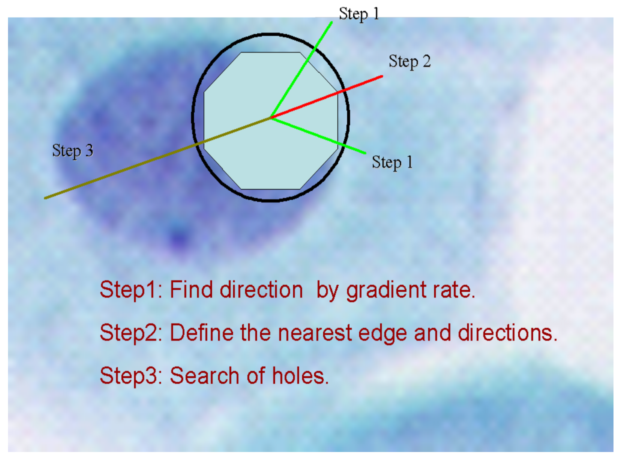

Fig. 9. Mask of the space-oriented filter with an image.

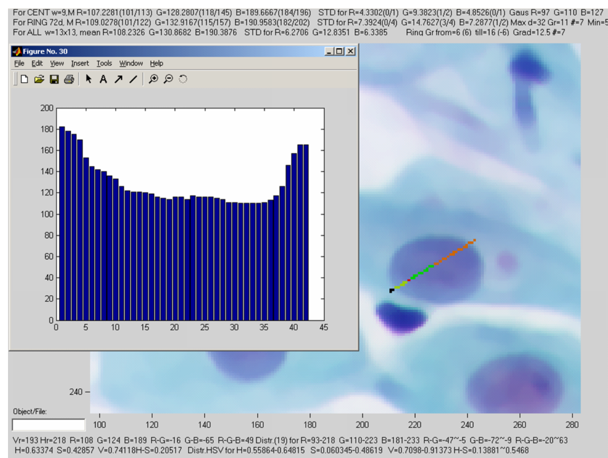

Fig. 10. Result of applying the space oriented filter to an image.

Calculation of the central of kernel

The centre calculation algorithm is based on the weighted mean from the total number of bars detected in the previous steps - Figure 3. The calculation depends on the kind of implementation used to design the processing engine. If the calculations are implemented in a programmed logic, the data are better stored in an index space. For a PC, the data are stored as array of coordinates.

Saving the index map (Figure 11)

After application of the algorithm, a connected area can be detected which serves as an index for further processing. An example of an index image is given in Figure 11 which includes the application of erosion and dilation for the subdivision of close located objects.

V. Two dimensional algorithm for image sharpening

In this section, we consider the procedures necessary during object recognition. These procedures are adaptive and are not bound to a particular range of applications.

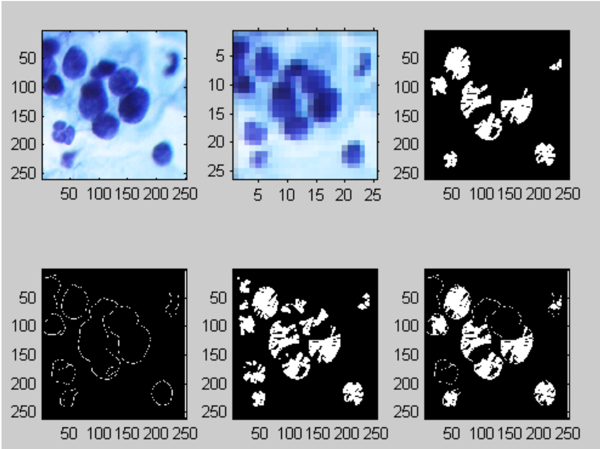

Fig. 11. Segmentation of nuclei (Index Image).

A. *Self-adjustable filter for enhanced object sharpness*

The task of edge searching of an object in an image is a part of the process of object recognition. In the case of an image with no preliminary information on the quantity of the points on each edge, resolution or particular boundary, it is possible to convert the data into an auxiliary map with an increased contrast range. With existing algorithms image contrast enhancement does not provide sufficient fidelity to cope with unknown levels of difference between objects. Typically, noise appears causing an increase in the level of transformation parameters and at a low level there is poor detection of an objects edge.

An image I, is represented in a computer memory in terms of an array $r \times c$ of points and the value of a particular point is determined as $I(r, c)$. One of the approaches to applying a filter or transformation to two-dimensional information representation is in terms of a sequence of masks M over $m \times n$ points and the subsequent calculation of a value for a central pixel depending on its environment. We now consider

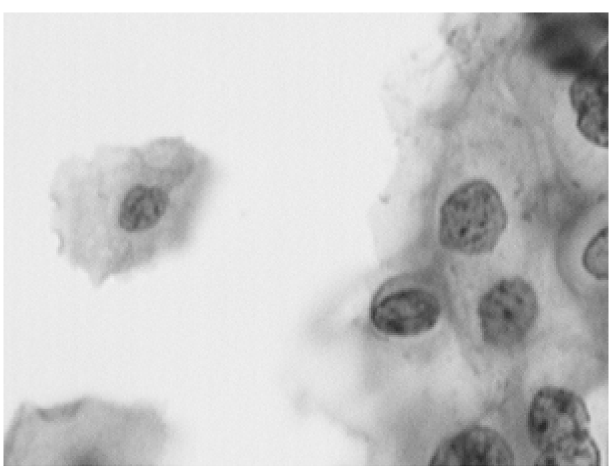

Fig. 12. Cytology cells - Mild dyskaryosis.

an algorithm for calculating the value of a central point in a moving window M with $m \times n$ points. The algorithm is applied sequentially and not recursively to all points of an image. For example, consider the image given in (Figure 12). The characteristic property of the given image is that during preparation of a sample, a cell can be fixed at a given angle and consequently, it can have a different gradient rate on different boundaries. The mask sizes m and n are selected according to the proportional sizes of the object to the image. The method is compounded in the following stages:

1. The first step is to sort out the array $M[m \times n]$ in terms of increasing values. The result of applying this operation gives an information represented in terms of a one-dimensional array $S[i]$ as illustrated in Figure 13.

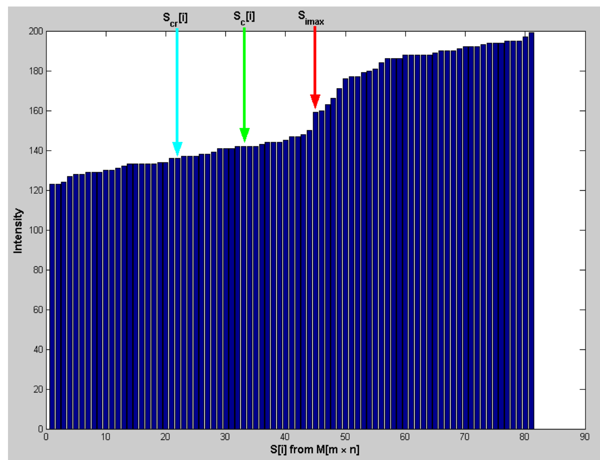

Fig. 13. Profile obtained by sorting an image into an array of increasing pixel values.

2. We define an index i as a point with the greatest value of a gradient rate S_{imax}. Otherwise, we determine a maximal gradient rate such that the given position of the window M does not correspond to a boundary of the object. It is then possible to apply general filtering methods, e.g. to calculate the average value or to take the value of a point with a predetermined index and with this value, assign it to a central point. For example, in Figure 13 S_{imax} is the point shown by the red arrow.
3. We estimate in which part of the sorted array $S[i]$ from mask M there exists a value of the original central mask point $I_c(r, c)$. For example, in Figure 13, this is indicated by the green arrow. We denote this part of the array by $S_c[i]$ (see Figure 13).
4. We estimate the parameter established by the user which sets a factor on a boundary excretion - in percentage terms, 50% for example - and then define the value of point $S_{cr}[i]$ of the array $S_c[i]$ from the beginning of the array. This value is the resultant solution $I_c(r, c) = S_{cr}[i]$ displayed by the cyan arrow in Figure 13.

An example result of applying this procedure is shown in Figure 14. Application of this filter allows us to observe very precisely the evolution of cell boundaries during the operation of the object recognition system.

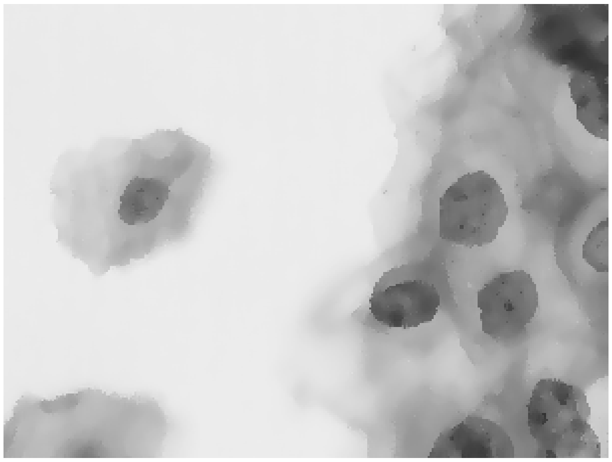

Fig. 14. Filtered image.

VI. Precision calculations on the measure of structure

For characterization, the line of objects obtained using the method described in the previous section, need to be considered in terms of their major properties. The modern requirements for recognition systems establish structures as main features for natural objects such as the measures defined by Tamura [9].

For structure classification, we apply fractal geometry for a description of natural objects. A fundamental property of a fractal is its Fractal Dimension. There are a number ways to calculate this feature of a fractal object and many different approaches to computing the Fractal Dimension have been considered [23]. For example, the origins of the 'box dimension' is hard to trace but would have been considered by pioneers of the Hausdorff measure and dimension and was probably rejected as being less satisfactory from a computational viewpoint. The precision of the calculation is less than two decimal places. Computation of the Fourier dimension provides a better result [10]. However, in our case, we have to estimate the dimension from an image with a lower resolution than that at which the object 'exists' using a frequency spectrum that is subject to additive noise.

Many signal processing applications are based on the use of different transforms. The signals under consideration are written as a linear combination (or series) of some predefined set of functions. Traditionally, orthogonal basis functions have been used for this purpose, for example, the discrete Fourier transform. The theory for orthogonal basis and Hilbert spaces can, however, be generalized to other sequences of functions called frames which have been used in this work to develop measures of structure with high precision.

If we consider the profile of a typical cytopathology image, then the curve does not coincide with a sine-wave signal. To obtain adequate accuracy, it is necessary to magnify the resolution of the image, which in turn introduces distortion. For increased accuracy on low-resolution data, we consider a convolution function of a form more consistent with the profile of a video signal. For a signal I we consider the representation

$$F(k) = \sum_{n=1}^{N} I(n)$$
$$\arccos\left[\cos\left(\frac{2\pi(\mathrm{k}-1)(\mathrm{n}-1)}{N} - \frac{\pi}{2}\right)\right] - \frac{\pi}{2}$$
$$-i \arcsin\left[\cos\left(\frac{2\pi(\mathrm{k}-1)(\mathrm{n}-1)}{N}\right)\right]$$

and for an image I with resolution $m \times n$,

$$F(p,q) = \sum_{m=1}^{M}\sum_{n=1}^{N} I(m,n) \tag{1}$$
$$\left(\arccos\left[\cos\left(\frac{2\pi(p-1)(m-1)}{M} - \frac{\pi}{2}\right)\right] - \frac{\pi}{2}\right)$$
$$\times\left(\arccos\left[\cos\left(\frac{2\pi(k-1)(n-1)}{N} - \frac{\pi}{2}\right)\right] - \frac{\pi}{2}\right)$$
$$-i \arcsin\left[\arccos\left(\frac{2\pi(k-1)(p-1)}{M}\right)\right]$$
$$\times \arcsin\left[\cos\left(\frac{2\pi(k-1)(n-1)}{N}\right)\right] \tag{2}$$

In this work, application of the power spectrum method used to compute the fractal dimension of a cell boundary and cell surface is based the above representations for $F(k)$ and $F(p,q)$ respectively. We then consider the power spectrum of an ideal fractal signal given by $P = c|k|^{-\beta}$, where c is a constant and β is the spectral exponent. In two dimensions, the power spectrum is given by $P(k_x, k_y) = c|k|^{-\beta}$, where $|k| = \sqrt{k_x^2 + k_y^2}$. In both cases, application of the least squares method or Orthogonal Linear Regression yields a solution for β and c [23], the relationship between β and the Fractal Dimension D_F being given by [23]

$$D_F = \frac{3D_T + 2 - \beta}{2}$$

for Topological Dimension D_T. This approach allows us to drop the limits on the recognition of small objects since application of the FFT (for computing the power spectrum) works well (in terms of computational accuracy) only for large data sets, i.e. arrays sizes larger than 256 and 256×256. Tests on the accuracy associated with computing the fractal dimension using equations (1) and (2) show an improvement of 5% over computations based on conventional Discrete Fourier Transform.

VII. Feature Determination

Features (which are typically compounded in a set of metrics - floating point or decimal integer numbers) describe the object state in an image and provides the input for a decision making engine as illustrated in Figure 2. The features considered in this paper are computed in the spatial domains of the original image $\{f_{m,n}\}$ and transformed image $\{\tilde{f}_{m,n}\}$. Further, these features are extracted from the three colour channels - Red (R), Green (G) and Blue (B) - captured by the CCD array. The issue of what type and how many features should be used to develop a computer vision system is critical to the design associated with a specific application. The system considered here has been developed to include features associated with the texture of an object which include the Fractal Dimension. Texture is particularly important in medical image classification and of primary importance in the application considered in this paper. The following features or their derivatives have been considered (primarily through a process of 'trial and error') in the recognition system reported in this paper:

Average Gradient G
: describes how the intensity changes when scanning from the object center to the border. The object gradient is computed using the least squares method in polar coordinates as compounded in the following result:

$$g = \frac{N \sum_{(m,n)\in S} r_{m,n}\tilde{f}_{m,n} - \sum_{(m,n)\in S} r_{m,n} \sum_{(m,n)\in S} \tilde{f}_{m,n}}{N \sum_{(m,n)\in S} r^2_{m,n} - \left(\sum_{(m,n)\in S} r_{m,n} \right)^2},$$

where N is the number of object pixels and $r_{m,n}$ is the distance between (m,n) and the center (m',n'), i.e.

$$r_{m,n} = \sqrt{(m-m')^2 + (n-n')^2}.$$

The centers (m',n') correspond to the local maximums of $\tilde{f}_{m,n}$ within the cluster. The cluster gradient is the average of object gradients,

$$G = \langle g_i \rangle_{i\in I}$$

where $i \in I$ is the object index.

Colour Composites Υ and Υ^D
: characterises the relationship between R, G and B layers of the transformed image. The triangle formula

$$r(a,b,c) = \sqrt{\frac{(s-a)(s-b)(s-c)}{s}},$$

$$s = \frac{1}{2}(a+b+c)$$

is applied to the 'colour triangle' RGB such that the following pixel colour composite is obtained

$$\upsilon_{m,n} = r(a,b,c)$$

where

$$a = \tilde{f}^R_{m,n}, \quad b = \tilde{f}^G_{m,n}, \quad c = \tilde{f}^B_{m,n}$$

and $\upsilon^D = r_{\text{incircle}}(a,b,c)$ with

$$a = |\tilde{f}^R_{m,n} - \tilde{f}^G_{m,n}|, \quad b = |\tilde{f}^G_{m,n} - \tilde{f}^B_{m,n}|$$

and

$$c = |\tilde{f}^R_{m,n} - \tilde{f}^B_{m,n}|.$$

The average colour composites are then given by

$$\Upsilon = \langle \upsilon_{m,n} \rangle_{(m,n)\in S}, \Upsilon^D = \langle \upsilon^D_{m,n} \rangle_{(m,n)\in S}.$$

Fourier Dimension q
: determines the frequency characteristics of the object and is related to the fractal dimension D by $q = 4 - D_F$ [1], [2]. It represents a measure of texture [23] and is computed using the approach discussed in Section VI.

Lacunarity (Gap Dimension) Λ_k
: characterizes the way the 'gaps' are distributed in an image [2]. The gap dimension is, roughly speaking, the number of light or dark spots in the image. It is defined for the given degree k by

$$\Lambda_k = \left\langle \left| \frac{f_{m,n}}{\langle f_{m,n} \rangle} - 1 \right|^k \right\rangle^{\frac{1}{k}},$$

where $\langle f_{m,n} \rangle = \frac{1}{N} \sum f_{m,n}$ denotes the mean value. In the system described in this paper, an average of local lacunarities of the degree $k = 2$ is measured in the spatial and frequency domains.

Symmetry Features S_n and M
: are estimated by morphological analysis in three-dimensional space, i.e. two-dimensional spatial coordinates and intensity. A symmetry feature S_n is measured for a given degree of symmetry n (currently $n = \{2,4\}$). This value shows the deviation from a perfectly symmetric object, i.e. S_n is close to zero when the object is symmetric and $S_n > 0$ otherwise. Feature M describes the fluctuation of the centre or mass for pixels with different intensities; $M = 0$ for symmetric objects and $M > 0$ otherwise.

Structure γ
: provides an estimation of the 2D curvature of the object in terms of the following:

$$\gamma < 0, \text{if the object bulging is less than a threshold,}$$

$$\gamma = 0, \text{if the object has the standard bulging,}$$

$$\gamma > 0, \text{if the object has a higher level of bulging.}$$

Geometrical Features
: include the minimum R_{min} and maximum radius R_{max} of the object (or ratio $R_{\text{max}}/R_{\text{min}}$), object area S, object perimeter P (or ratio S/P^2) and the coefficient of infill S/S_R, where S_R is the area of the bounding polygon which, in this application, is determined using the convex hull algorithm given in Section V.

The system reported in this paper classifies objects using mixed mode features that are based on Euclidean and fractal geometric metrics. The procedure of object detection is performed at the segmentation stage and needs to be adjusted for each area of application. The recognition algorithm then makes a decision using a knowledge database and outputs a result by subscribing objects based on the features defined above. The 'expert data' associated with a given application creates a knowledge database by using a supervised training system with a number of model objects. This is discussed in the following section.

VIII. Object Recognition

In order to characterize an object, the 'system' must have a mathematical representation compounded in metrics that are used to compose a feature vector. The basis for the application considered in this paper are the textural features (Fourier dimension and Lacunarity) for an object coupled with the Euclidean and morphological measures as defined in the previous section. In the case of a general application, all objects are represented by a list of parameters for implementation of supervised learning in which a fuzzy logic engine automatically adjusts the weight coefficients for the remaining features. The methods developed represent a contribution to pattern recognition based on fractal geometry (at least in a partial sense), fuzzy logic and the implementation of a fully automatic recognition scheme as illustrated in Figure 15 for the Fractal Dimension D (just one element of the feature vector used in practice). The recognition procedure uses the decision making rules from fuzzy logic theory [21], [18], [19], [20] based on all, or a selection, of the features defined and discussed in Section VII which are combined to produce a feature vector $\mathbf{x}$.

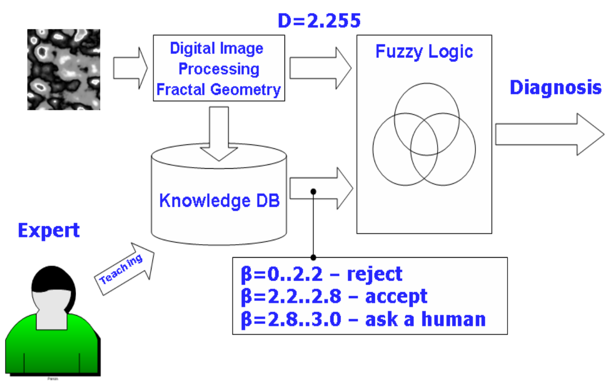

Fig. 15. Basic architecture of the diagnostic system based on the Fractal Dimension D (a single feature) and decision making criteria β.

A. Decision Making

The class probability vector $\mathbf{p} = \{p_j\}$ is estimated from the object feature vector $\mathbf{x} = \{x_i\}$ and membership functions $m_j(\mathbf{x})$ defined in the knowledge database. If $m_j(\mathbf{x})$ is a membership function, the following equation defines the probability for each j^{th} class and i^{th} feature as follows:

$$p_j(\mathbf{x}_i) = max\left[\frac{\sigma_j}{|\mathbf{x}_i - \mathbf{x}_{j,i}|} \cdot m_j(\mathbf{x}_{j,i})\right]$$

for weight coefficient matrix given by $w_j = w_{j,i}$ where σ_j is the distribution density of values $\mathbf{x}_j$ at the point $\mathbf{x}_i$ of the membership function. The next step is to compute the mean class probability given by

$$\langle p\rangle = \frac{1}{j}\sum_j \mathbf{w}_j p_j$$

where the distance from the mean probability selects the class associated with

$$p(j) = min\left[(p_j \cdot \mathbf{w}_j - \langle p\rangle) \geq 0\right]$$

providing a result for the decision making of the j^{th} class. The weight coefficient matrix is adjusted during the learning stage of the algorithm.

The decision criterion method considered here represents a weighing-density minimax expression. The estimation of the decision accuracy is achieved by using the density function

$$d_i = |\mathbf{x}_{\sigma_{max}} - \mathbf{x}_i|^3 + (\sigma_{max}(\mathbf{x}_{\sigma_{max}}) - p_j(\mathbf{x}_i))^3$$

with an accuracy determined by

$$P = \mathbf{w}_j p_j - \mathbf{w}_j p_j \frac{2}{\pi}\sum_{i=1}^{N} d_i.$$

B. Supervised Learning Process

The supervised learning procedure is the most important part of the system for operation in automatic recognition mode. The training set of sample objects should cover all ranges of class characteristics with a uniform distribution together with a universal membership function. This rule should be taken into account for all classes participating in the training of the system. An expert defines the class and accuracy for each model object where the accuracy is the level of self confidence that the object belongs to a given class. During this procedure, the system computes and transfers to a knowledge database a vector of values of parameters $\mathbf{x} = \{x_i\}$ which forms the membership function $m_j(\mathbf{x})$. The matrix of weight factors $w_{j,i}$ is formed at this stage accordingly for the i^{th} parameter and j^{th} class using the following expression:

$$w_{i,j} = \left|1 - \sum_{k=1}^{N}\left(p_{i,j}(\mathbf{x}_{i,j}^k) - \langle p_{i,j}(\mathbf{x}_{i,j})\rangle\right) p_{i,j}(\mathbf{x}_{i,j}^k)\right|.$$

The result of the weight matching procedure is that all parameters which have been computed but have not made any contribution to the characteristic set of an object are removed from the decision making algorithm by setting $w_{j,i}$ to null.

IX. Discussion

The methods discussed in the previous sections represent a novel approach to designing an object recognition system that is robust in classifying textured features, the application considered in this paper, having required a symbiosis of the parametric representation of an object and its geometrical invariant properties. In comparison with existing methods, the approach adopted here has the following advantages:

Speed of operation. The approach uses a limited but effective parameter set (feature vector) associated with an object instead of a representation using a large set of values (pixel values, for example). This provides a considerably higher operational speed in comparison with existing schemes, especially with composite tasks, where the large majority of methods require object separation. The principal computational effort is that associated with the computation of the feature vector using the metrics discussed in Section VII

Accuracy. The methods constructed for the analysis of sets of geometrical primitives are, in general, more precise. Because the parameters are feature values, which are not connected to an orthogonal grid, it is possible to design different transformations (shifts, rotational displacements and scaling) without any significant loss of accuracy compared with a set of pixels, for example. On the other hand, the overall accuracy of the method is directly influenced by the accuracy of the procedure used to extract the required geometrical tags. Generally, the accuracy of a method will always be lower, than, for example, classical correlative techniques, where, due to padding, error can arise during the extraction of a parameter set. However, by using precise parameterization structures based on fractal geometry, remarkably good results are obtained.

Reliability. The proposed approach relies first and foremost on the reliability of the extraction procedure used to establish the geometrical and parametric properties of objects, which, in turn, depends on the quality of the image; principally in terms of the quality of the contours. It should be noted, that the image quality is a common problem in any visual system and that in conditions of poor visibility and/or resolution, all vision systems will fail. In other words, the reliability of the system is fundamentally dependent on the quality of the input data.

An additional feature of the system discussed in this paper, is that the sub-products of the image processes can be used for tasks that are related to image analysis such as a search for objects in a field of view, object identification, maintaining an object in a view field, optical correction of a view point and so on. These can include tasks involving the relative motion of an object with respect to another object or with respect to background for which the method considered can be also be applied - collision avoidance tasks, for example.

Among the characteristic disadvantages of the approach, it should be noted that: (i) The method requires a considerable number of different calculations to be performed and appropriate hardware requirements are therefore mandatory in the development of a real time system; (ii) the accuracy of the method is intimately connected with the required computing speed - an increase in accuracy can be achieved but may be incompatible with acceptable computing costs. In general, it is often difficult to acquire a template of samples under real life or field trial conditions which have a uniform distribution of membership functions. If a large number of training objects are non-uniformly distributed, it is, in general, not possible to generate accurate recognition system.

The original approach to the decision process proposed includes the following important steps: (i) estimation of the density distribution is accurately determined from the original samples in the membership function during a supervised learning phase which improves the recognition accuracy under non-ideal conditions; (ii) the pre-filtering procedures provide a good response to the required features of the object without generating noise; (iii) the segmentation procedures discussed in Section III efficiently select only those objects required; (iv) computation of fractal parameters, in particular, the average lacunarity, helps to characterize the textural features (in terms of their classification) associated with the object.

The integration of Euclidean with fractal geometric parameters provides a more complete suite of tools for pattern recognition in combination with supervised learning through fuzzy logic criteria. In the following section, we consider the application of our approach for the design of a cytological screening system.

X. Application to cervical smear screening

The application considered in this section has focused on screening programmes that utilize Liquid Based Cytology (LBC). Cells are collected from the cervix in the same way as PAP smear, but using a very small brush instead of a spatula. The head of the brush is broken off and maintained in a liquid environment instead of smearing the cells directly onto a slide. This preserves the cells and so the results of the test are more reliable. At present, about one in twelve PAP smears have to be done again because they can not be read properly. With the LBC approach, far fewer test have to be repeated. However, the LBC method is not, as yet, in widespread use. Nevertheless, the system reported in this paper has been designed to operate in conjunction with screening centres that use LBC.

A. Classes of Cervical Cells

There are two main types of cervical cancer: (i) Squamous cell cancer; (ii) Adenocarcinoma. They are named after the type of cell that becomes cancerous. Squamous cells are the flat skin-like cells that cover the surface of the cervix. Squamous cell cancer is the most common type of cervical cancer. Adenocarcinoma cells are glandular cells that produce mucus. The cervix has these glandular cells along the inside of the passageway that runs from the cervix to the womb (the endocervical canal). Adenocarcinoma is a cancer of these cell types. It is less common than squamous cell cancer, but has become more commonly recognised in recent years. Only about one in five to one in ten cases of cervical cancer are adenocarcinoma. Adenocarcinoma is associated with a similar precancerous phase. It is treated in the same way as squamous cell cancer of the cervix.

Tables I and II explain the relationship between the current system and Bathesda 2001 classifications - http://www.aafp.org/afp/2003/1115/p1992.html. The first class represents normal cells and the last one are malignant (cancerous) cells. Intermediate classes represent different degrees of abnormalities; it is important to detect these as well. The classification, for which the system is 'focused' is simplified because, unlike Bathesda 2001, it provides a *fuzzy* estimation of class membership, which gives a better description of the cell state. An additional class *Exudate* is defined to described irrelevant structures in the image.

With current techniques, all cervical smear tests are examined by 'screeners' who have only a few minutes per slide. This means that the screening is done at low magnification and high speed so it is not surprising that mistakes can be made. The 'screeners' look for abnormal variations in the ratio of the

TABLE I

CLASSIFICATION OF SQUAMOUS CELLS.

System	Bathesda 2001
Normal Sq	Normal squamous cells
Normal Sq	Atypical squamous cells – 'undetermined significance' (ASC-US)
Normal Sq	Atypical squamous cells – 'cannot exclude high grade disease' (ASC-H)
LSIL	Low grade squamous intra-epithelial lesion (LSIL)
HSIL	High grade squamous intra-epithelial lesion (HSIL) – CIN2
HSIL	High grade squamous intra-epithelial lesion (HSIL) – CIN3
Invasive Sq	Invasive squamous carcenoma

TABLE II

CLASSIFICATION OF GLANDULAR CELLS.

System	Bathesda 2001
Normal Gl	Normal glandular cells
Normal Gl	Atypical glandular cells (AGC) – endocx/endom/not specified
Normal Gl	Atypical glandular cells (AGC) – favour neoplasia
AIS	Adenocarcinoma in situ (AIS)
Invasive Adeno	Adenocarcinoma

size of the nucleus relative to the size of the cell, as well as other markers of diseased tissue. When they identify suspect areas of the slide they mark these with a felt tip pen and pass them on for further inspection. These slides are then looked at by 'checkers' who have more experience and examine the slide more carefully and at higher magnification. If they are not satisfied that 'all is well', then they pass the suspect slides to a cytopathologist for further, more detailed analysis and diagnosis. Even at this final stage, mistakes can be made as each slide is prepared differently and it is common for cells to overlie each other, compounding the problem of accurate diagnosis further. New techniques that use cytocentrifuge preparations (e.g. http://www.tharmac.com/?p=15) can overcome this last problem but have yet to be introduced in general.

One of the major criteria of assessing whether a cell is premalignant or malignant is the ratio of the size of the nucleus of the cell compared with that of the whole cytoplasm - the nuclear/cytoplasmic ratio. The rapid identification of variations in these ratios enables 'checkers' to quickly and more accurately determine if there are abnormalities by examining cells that are located in a small area. To estimate the condition of the cells, the cytologist typically makes upto 300 slide movements over a period of 8-10 minutes on a desk microscope and may consequently miss many important features. This approach not only takes time but inevitably can not guarantee consistent and accurate estimates of the condition of the cells. With an increasing number of screening projects taking place together with the variability of different preparations, diagnostic errors can lead to a number of fatalities due to false negatives and lack of appropriate treatment in the early stages of cervical cancer.

At present, there are no commercial or experimental systems available for the automatic identification and classification of tissue cells without human participation. Obtaining results from cytology diagnostics in real time with a robust least error criterion is a widespread and important problem for screening the cervix uteri. The automatic coloring (staining) and scanning of the material creates preconditions in designing an algorithm and technical devices for the automatic identification and classification in cytopathology. A key point is to identify and classify the condition of the cell nuclei using a suitable recognition process.

There are a range of techniques that aim to improve the examination of slides using integrated optical densitometry. For example, SurePath - http://www.pathlabsofark.com/surepathliquidpap.html - uses integrated optical density of conventional smears. The aim of the system reported in this paper is to exclude 25% of samples without visual examination. Unlike a human expert, the automatic scanning method can count the cells and estimate their statistical distribution among classes or states. The system delivers high accuracy and automation due to the following innovations:

Fractal analysis
: Biological structures (such as body tissues) have natural fractal properties. Numerical measurements of these properties provides for the efficient and effective detection of abnormalities.

Extended set of detectable features
: High accuracy is achieved when multiple features are measured together and combined into a result

Advanced fuzzy logic engine
: The knowledge-based recognition scheme enables highly accurate diagnosis.

B. System Overview

It is proposed that the approach described in this paper and the system developed may assist cytopathologists in reducing the workload by eliminating in a secure manner a percentage of normal smears, thus allowing more time for the evaluation of the abnormal cases. The 'software solutions' detect abnormalities in organic structures such as cells by digital image analysis. Cancer experts create the knowledge database by training the system with a number of case study images. The recognition algorithm is composed of the following steps:

Filtering
: The image is filtered to reduce noise and remove unnecessary features (bacteria, broken cells).

Segmentation
: The image is segmented to perform a separate analysis of each object. In order to separate connected objects a new algorithm has been designed. An example of the GUI developed is given in Figure 16 which shows the stage at which the nuclei of suspect cells have been identified and located.

Feature Detection
: For each object, a set of recognition features are detected. The features are numeric parameters that describe the object inclusive of fractal geometric parameters. The system captures a variety of geometrical, fractal and statistical features in one- and two-dimensions. One-dimensional features correspond to

TABLE III
IMAGING ACQUISITION HARDWARE.

Model and Supplier	Advantages	Shortcomings
Nikon Coolscope (Nikon Instruments Europe BV)	Available on the market Magnification 40x. Complete solution with a slide feeder.	Very slow (several hours/slide). Small focus depth and automatic focus does not find the optimal z-position. Dynamic range to be adjusted. Tiling scan.
Aperio Scanscope (Aperio Technologies: DakoCytomation)	High scanning speed (20 min/slide). Magnification 40x. Non-tiling scan. Better focus. Better dynamic range.	Not fully developed. Problem to achieve 60x.
Nikon Eclipse E8000 + JVC 3-CCD KY-F55B.	Variable resolution 4X-80X. Manual focus. Manual brightness.	Manual image capture. Can be used only for testing.

the border of objects, whereas two-dimensional features relate to the surface within and around objects.

Decision Making

The system uses fuzzy logic to combine features into a decision. A decision is the estimated class of object and accuracy probability. In-between states are determined by the probability. For example, 35% normal is equivalent to 65% abnormal and suggests careful analysis by cancer specialists. In the extended training version for cervical cancer, the system provides upto 10 classes (CINs) depending on the classification system and the number and extent of available samples for learning procedures.

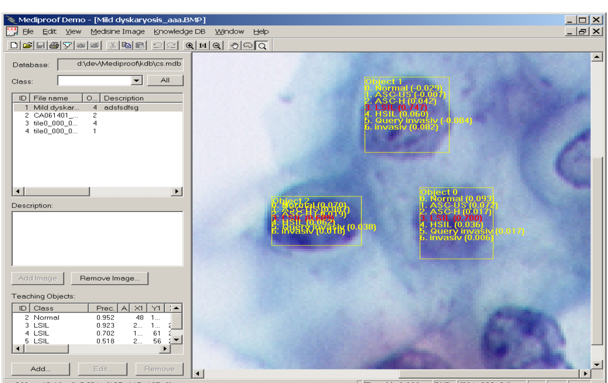

Fig. 16. GUI associated with the cervical smear analysis system.

The system has been developed to operate with a range of image acquisition hardware, examples of which are provided in Table III.

XI. Conclusion

This paper has been concerned with the task of developing a methodology and implementing applications that are concerned with two key tasks: (i) the partial analysis of an image in terms of its fractal structure and the fractal properties that characterize that structure; (ii) the use of a fuzzy logic engine to classify an object based on both its Euclidean and fractal geometric properties. The combination of these two aspects has been used to define a processing and image analysis engine that is unique in its modus operandi but entirely generic in terms of the applications to which it can be applied.

The research has investigated numerous processes for pattern recognition using fractal geometry as a central processing kernel. This has led to the design of a new library of pattern recognition algorithms. The image types considered contain about 80% useful environmental information for the human. With rapid advances in video technology, the content of a video stream is increasing at a rate that is far beyond the human brain capacity for decision making. This necessitates a need for developing an automatic image processing and decision making system using artificial intelligence. Such systems are required in search engines, information databases, navigation in unknown terrain, interpretation of two dimensional data, etc.

The creation of logic and general purpose hardware for artificial intelligence is a basic theme for any future development based on the results reported in this paper for the applications developed and beyond. The results of the current system can be utilized in a number of different areas although medical imaging would appear to be one of the most natural fields of interest because of the nature of the images available, their complex structures and the difficulty of obtaining accurate diagnostic results which are efficient and time effective. A further extension of our approach is to consider the effect of replacing the fuzzy logic engine used to date with an appropriate Artificial Neural Network. It is not clear as to whether the application of an ANN could provide a more effective system and whether it could provide greater flexibility with regard to the type of images used and the classifications that may be required. Within the context of this paper, algorithms have been designed that focus on solving the detection and classification problems associated with the analysis of cervical smear images. In this respect, a new set of image processing algorithms have been developed that may have value in a wider class of image processing and pattern recognition application, particularly with regard to medical image analysis.

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