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Pattern Recognition in Cytopathology for Papanicolaou Screening

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Abstract

A unique space oriented filer is presented in order to detect and isolate the cell of a nucleus for applications in cytopathology. A classification method for nuclei is then considered based on the application of a set of features which includes certain fractal parameters. Segmentation algorithms are considered in which a self-adjustable sharpening filter is designed to enhance object location. Although the methods discussed and the algorithms developed have a range of applications, in this work we focus the engineering of a system for automating a Papanicolaou screening test using standard optical images

Categories and Subject Descriptors (according to ACM CCS): F.2.2; I.5.4 [Pattern recognition]: Segmentation, Contour detection, Decision making, Self-learning, Cytopathology.

1. 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 and it remains among the most common female cancers in many countries.

1.1. 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.

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

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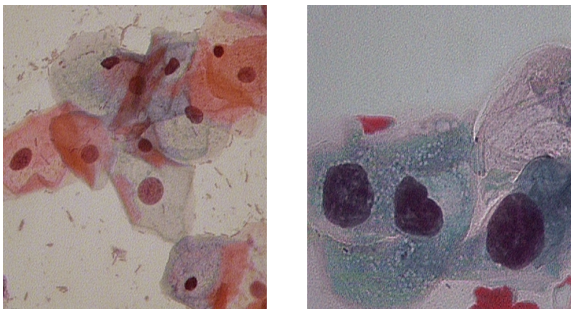

Figure 1: *Example of normal (left) and abnormal cell clusters (right) where, in the latter case, the Cytoplasm-to-Nuclei area ratio is reduced.*

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 up to 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.

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 where an increase in either reduces the speed and reliability of the results. Telecytology [JM06] provides a large number of digital images for consideration which can increase 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 [WB07], [MR08], [YJ05]. 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.

1.2. 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 [Bla06], [Bla05]. 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 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. [E.R97], [Fre88], [LG90], [SQ04, J.S90].

Machine 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. The levels of representation are dependent on what type of segmentation can and/or should be applied to an image and are based on how humans interpret images, but the nature of this interpretation is not always clear. 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 using a new segmentation (edge detection) algorithm based on a space-oriented filter that incorporates a contour tracing algorithm developed previously [JD08]. The image usually requires enhancement before it is processed and, for this purpose, a novel self-adjusting sharpening filter has been designed as discussed in this paper. 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.

2. 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.

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 [JM98], [Bla06], [Bla05]. 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. The recognition process is illustrated in Figure 2, a process that includes the following steps:

1. Image Acquisition and Filtering
   A physical object is digitally imaged and the data transferred to memory using image acquisition hardware that is 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 [NB86]. 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 [JD08].
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

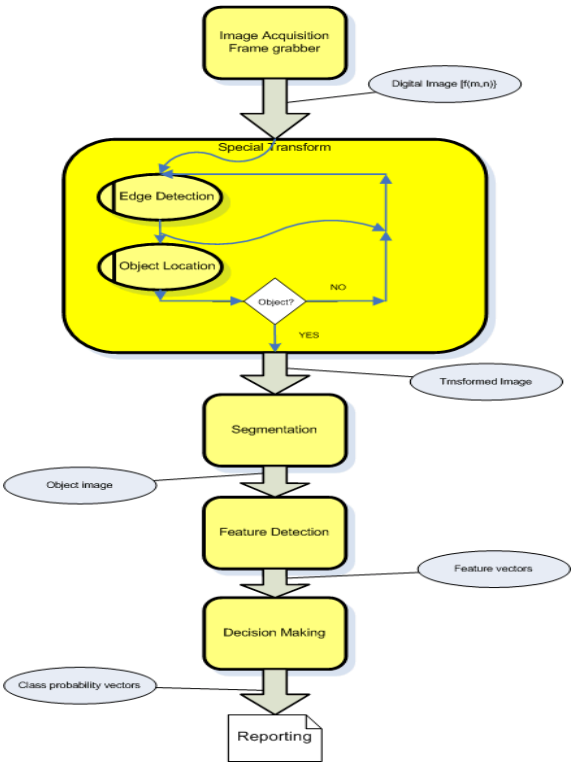

Figure 2: *Recognition processes.*

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 [Vad93]. Probability theory and fuzzy logic [Mam76] 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 [San76].

The application considered in this paper is based on algorithms that have been designed to solve problems associated with the above steps. Details of these algorithms are given in [JD08] 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 may be considered as an intermediate mask filter in order to clarify a cellular border. For characterisation, 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 manual operation. 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 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 3 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.

3. 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 positions in the image where the intensity changes rapidly; this is typically based on using one of two principal criteria:

- areas where the first derivative of the intensity is larger in magnitude than some threshold;
- 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 is usually present, we consider an appropriate adaptive filtering strategy. 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.

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 [J.C86] is used to provide a first estimate of the edge boundaries of a cell nucleus.

In some cases, the nuclei of the cells in a cervical smear image 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 3. 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 4. To start with, we estimate the brightness

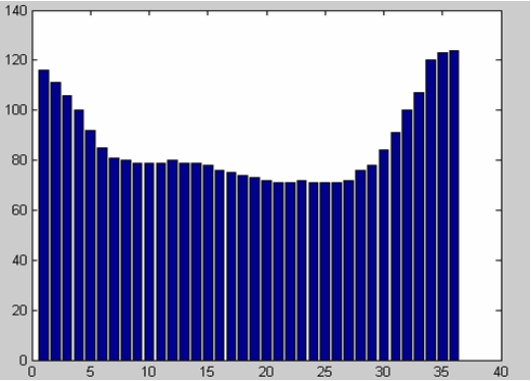

Figure 3: *Example intensity profile of a cell Nucleus.*

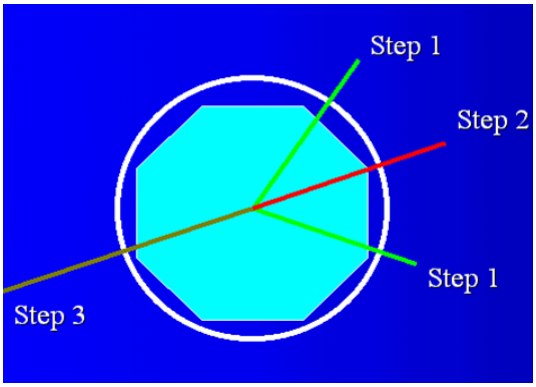

Figure 4: *Mask used for space-oriented filtering.*

of the central area (using a window of 9×9 pixels) and a circle (a layer consisting of 2 pixels). If the centre is dark, we suppose that it is part of the nuclei and compare the intensity along the white line in Figure 4 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 4). This hole detection algorithm is extended in a procedure to decide whether the area under investigation is a nucleus or otherwise. In Figure 4, the 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 centre 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 centre of a hole up to the border of a hysteresis is drawn. To automatically find the edges between all 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:

- estimation of the edge;
- search the boundaries of the cell;
- calculate the direction to the centre of a core;
- search the opposite edge of the core;
- calculate the centres of the kernels;
- 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 4. This selects only those nuclei of interest and avoids spending computer time processing other parts of the image.

Searching the Boundaries of the Cell

The ring around of the central part of a mask (Figure 4) is decomposed using the operator

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

In the following analysis, we evaluate the gradient sequence

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

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

Calculation of the Direction of the Centre

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

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

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

The mask is applied in the direction of a local gradient rate and gives a maximal convolution between both points obtained in the search for the boundaries of the cell. 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 for the process discussed below where the dimension $I_B(r,c)$ corresponds to the dimension and starting map $I_g(r,c)$.

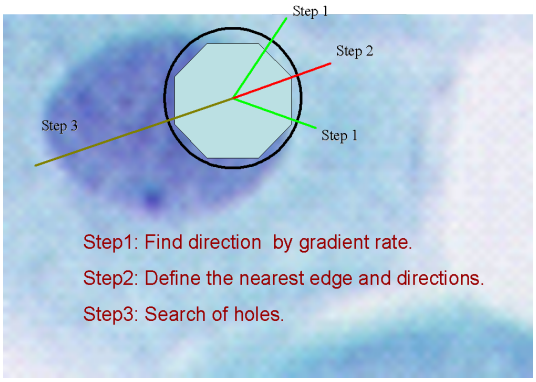

Figure 5: *Mask of the space-oriented filter with an image.*

Search for the Opposite Edge of a Core

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 the object. In Figure 5 these lines are illustrated in brown. The opposite profile has to have the same properties as those generated in the calculation undertaken to determine the direction of the a cell's centre. This prevents any detection error through irregularities in the image. If the opposite profile is found, then a 'green line' is 'painted' on the index binary image from the centre to the boundary of the nucleus as shown in Figure 6.

Calculation of the Kernel Centre

The centre calculation algorithm is based on the weighted mean from the total number of 'bars' detected in the previous steps. 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 an array of coordinates.

Saving the Index Map

After application of the algorithm, a connected area can be detected which serves as an index for further processing.

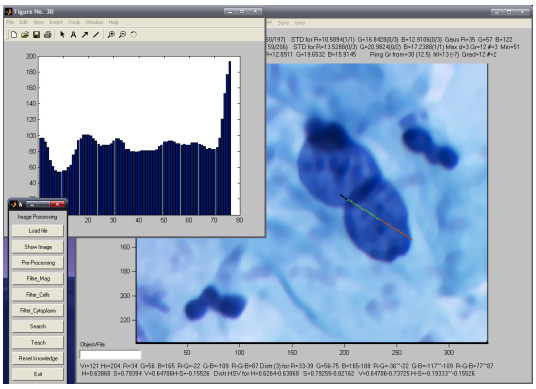

Figure 6: *Result of applying the space oriented filter to an image.*

4. Self-adjustable Filter for Object Sharpening

We consider the procedures necessary during object recognition. These procedures are adaptive and are not bound to a particular range of applications. 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 a 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 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 7). The characteristic property of the given image depends of the 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 steps:

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 information represention in terms of a one-dimensional array $S[i]$ as illustrated in Figure 8.
2. We define an index i as a point with the greatest value of

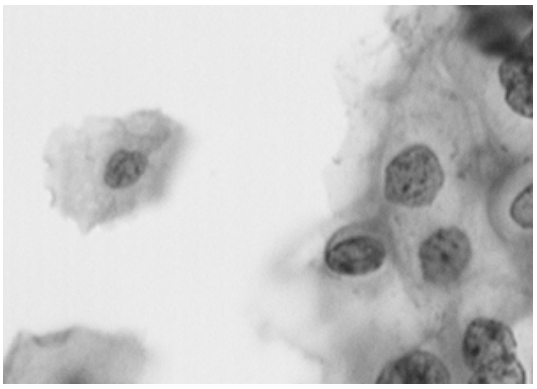

Figure 7: *Cytology cells - Mild dyskaryosis.*

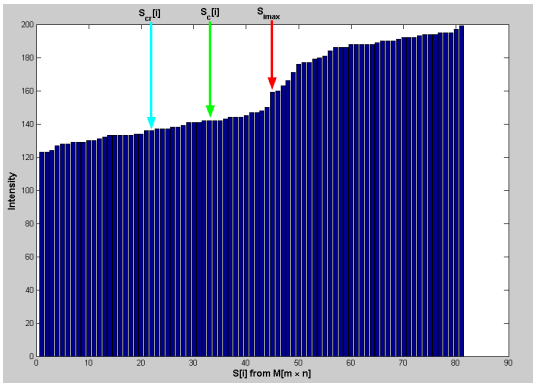

Figure 8: *Profile obtained by sorting an image into an array of increasing pixel values.*

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 8 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 8, this is indicated by the green arrow. We denote this part of the array by $S_c[i]$ (see Figure 8).
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 start of the array. This value is the resultant solution $I_c(r,c) = S_{cr}[i]$ displayed by the cyan arrow in Figure 8.

An example result of applying this procedure is shown in Figure 9. Application of this filter allows us to observe very precisely the evolution of cell boundaries during the object recognition process.

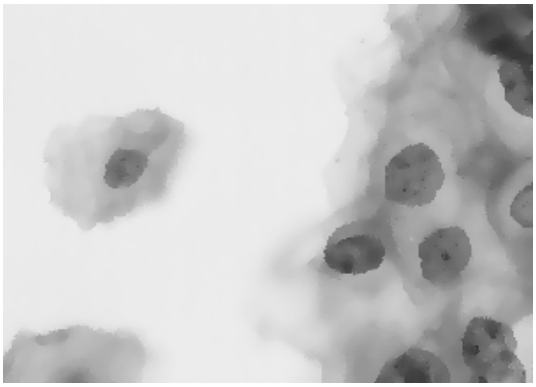

Figure 9: *Filtered image.*

5. Feature Selection, Leaning and 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 determination of which particular element of a feature vector are useful with regard to the application considered (i.e. cell nuclei classification) is based on the self-leaning algorithm discussed in [JD09]. The basis for the application considered in this paper are the textural features (Fractal dimension and Lacunarity) of an object coupled with Euclidean parameters and morphological measures. 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 recognition procedure uses the decision making rules from fuzzy logic theory [Vad93, Zad75, Mam76, San76] based on all, or a selection, of the features defined in [JD09] which are combined to produce a feature vector x_i.

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 a 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:

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

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 [JD09].

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:

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

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.

6. Conclusion

This paper has been concerned with the task of developing a methodology and implementing applications that are concerned with the following tasks: (i) space oriented segmentation; (ii) object sharpening for object location; (iii) the use of a fuzzy logic engine to classify an object based on both its Euclidean and Fractal geometric properties using a feature vector based on the measure discussed in [JD09]. The combination of these aspects has been used to define a processing and image analysis engine that is specific in its modus operandi with regard to the problem of automating a Papanicolaou screening test using standard optical images.

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