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Object Detection and Classification with Applications to Skin Cancer Screening

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***Abstract*— This paper discusses a new approach to the processes of object detection, recognition and classification in a digital image. The classification method is based on the application of a set of features which include fractal parameters such as the Lacunarity and Fractal Dimension. Thus, the approach used, incorporates the characterisation of an object in terms of its texture.**

The principal issues associated with object recognition are presented which includes two novel fast segmentation algorithms for which C++ code is provided. The self-learning procedure for designing a decision making engine using fuzzy logic and membership function theory is also presented and a new technique for the creation and extraction of information from a membership function considered.

The methods discussed, and the 'system' developed, have a range of applications in 'machine vision'. However, in this publication, we focus on the development and implementation of a skin cancer screening system that can be used in a general practice by non-experts to 'filter' normal from abnormal cases so that in the latter case, a patient can be referred to a specialist. A demonstration version of the application developed for this purpose has been made available for this publication which is discussed in Section IX.

***Index Terms*— Computer vision, Segmentation, Object recognition, Contour tracing, Decision making, Self-learning, Fuzzy logic, Image morphology, Skin cancer screening.**

I. INTRODUCTION

IMAGE analysis 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 [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 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 understanding 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, recognition and classification in an independent environment, e.g. [3], [4], [5], [7].

Vision can be thought of as the process of linking parts of the visual field (objects) with stored information or 'templates' with regard to a pre-determined 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 affect 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 primal sketches 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, 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 data base 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

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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 scene that is based on a new segmentation algorithm for edge recognition using a Contour Tracing Algorithm. This algorithm differs from conventional 'edge detection' techniques in two respects: (i) it is not based on detecting first or second order gradients in an image using conventional FIR filters [2]; (ii) it is independent of any binarisation process through application of a threshold. After detection, the object is analysed in terms metrics derived from both a Euclidean and fractal geometric perspective, the output fields being used to train a fuzzy inference engine. The recognition structure is based on some of the image processing, analysis and machine vision techniques reported in [6], for example. The approach considered is generic in that it can, in principle, be applied to any type of imaging modality for which there are numerous applications that include speech and image recognition where self-calibration and learning is often mandatory. Example applications may include remote sensing, non-destructive evaluation and testing and 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 skin cancer for screening patients through a general practice. The system reported is, in principle, just one of a number of variations which can be used for medical image analysis and classification in general. This is because the system includes features that are based on the textural properties of an image (defined in terms of fractal geometric parameters including the Fractal Dimension and Lacunarity) which is an important theme is medical image analysis.

II. Feature Detection and Classification

Suppose we have an image which is given by a function $f(x, y)$ and contains some object described by a set of features $S = \{s_1, s_2, ..., s_n\}$. We consider the case when it is necessary to define a sample which is somewhat 'close' to this object in terms of a matching set. 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. This process 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 aspects of each step, details of which are discussed in the following sections. In particular, we consider the design features and their implementation together with their advantages, disadvantages and proposals for a solution whose application, in this paper, focuses on the problem of designing a skin cancer screening system. It is for this reason, that the examples given to illustrate the steps proposed, are 'system related'.

Image acquisition depends on the technology that is best suited for integration with a particular application. For pattern recognition in histopathology, 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, e.g. an optical microscope. The colour images used in the current application discussed 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 through application of well diffused light sources. 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 and 'fine tuned' for each area of application. This includes those features associated with an object for which fractal models are well suited [1], [2], [14].

The system described in this paper provides an output (i.e. a decision) using a knowledge database which generates a result (a decision) by subscribing different objects. The 'expert data' in the application field creates a knowledge database by using supervised training with a number of model objects [9]. The recognition process is illustrated in Figure 1, a process that includes the following steps:

1) Image Acquisition and Filtering.
   A physical object is digitally imaged and the data transferred to memory, e.g. 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 segmentation and feature detection operations [8]. This transform avoids the use of conventional 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, edge or contour tracing (Section IV) and the convex hull method (Section V).
4) Feature Detection.

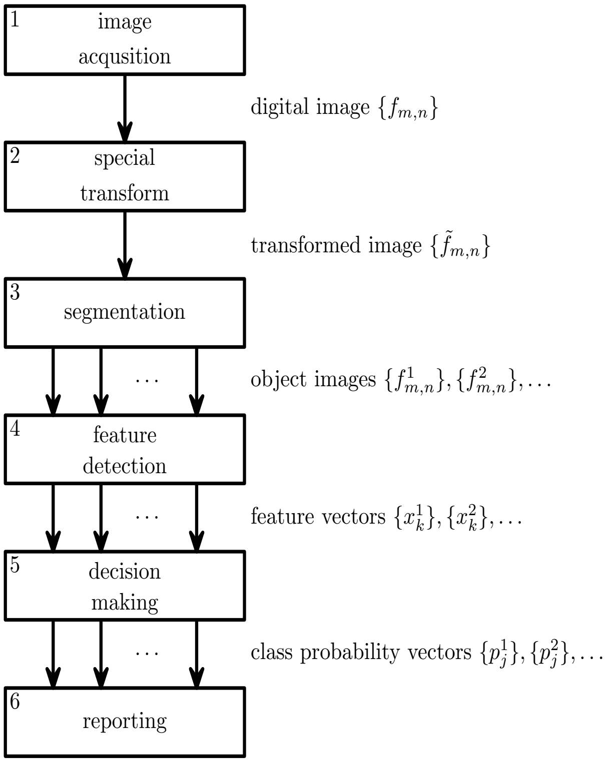

Fig. 1. Recognition process

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 transformed images $\{\tilde{f}^1_{m,n}\}, \{\tilde{f}^2_{m,n}\}, \ldots$. 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 [12]. Probability theory and fuzzy logic [10] are applied to estimate the class probability vectors $\{p^1_j\}, \{p^2_j\}, \ldots$ from the object feature vectors $\{x^1_k\}, \{x^2_k\}, \ldots$. A fundamental problem has been to establish a quantitative relationship between features and class probabilities, i.e.

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

where $\leftrightarrow$ denotes a transformation from class probability to feature vector space. A 'decision' is the estimated class of the object coupled with the probabilistic accuracy [11].

This paper reports on a number of new algorithms that have been designed to solve problems associated with the above steps. Two new morphological algorithms for object segmentation have been considered which include auto-threshold selection. One of these algorithms - a contour tracing algorithm - extracts parameters associated with the spatial distribution of an object's border. This algorithm is also deployed in the role of feature detection. Another algorithm, that is concerned with computing a boundary with the 'convex hull' property, has been designed for operation in an environment where we do not have preliminary information about object position and orientation.

With regard to the decision making engine, the approach considered 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 normal manual work. 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 on 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 the contour of an object with any level of complexity to produce an output that consists of a consecutive list of coordinates. The algorithm is optimised in terms of computational efficiency and can be realised in a compact form suitable for hardware implementation.

III. SEGMENTATION

Segmentation is implemented by adaptive thresholding and morphological analysis. The adaptive image threshold is given by

$$T = \begin{cases} T_x, & T_x \geq T_y; \\ T_y, & \text{otherwise}. \end{cases}$$

where

$$T_x = \frac{1}{2}\left(\min_y \left(\max_x f(x,y)\right) - \langle \max_x f(x,y)\rangle_y\right)$$

$$+\langle \max_x f(x,y)\rangle_y,$$

$$T_y = \frac{1}{2}\left(\min_x \left(\max_y f(x,y)\right) - \langle \max_y f(x,y)\rangle_x\right)$$

$$+\langle \max_y f(x,y)\rangle_x.$$

Here, $\langle\cdot\rangle_x$ 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 associated with a well defined object in the image frame. Thus, if an object covers an extensive image space, then this 'filter' provides the fastest compact solution. For example, in the skin cancer screening application considered here, there is preliminary information based on the fact that there is just one object on the image (as shown in the example given in Figure 2). In order to obtain a clear boundary, the morphological analysis applied here selects objects with a predefined area.

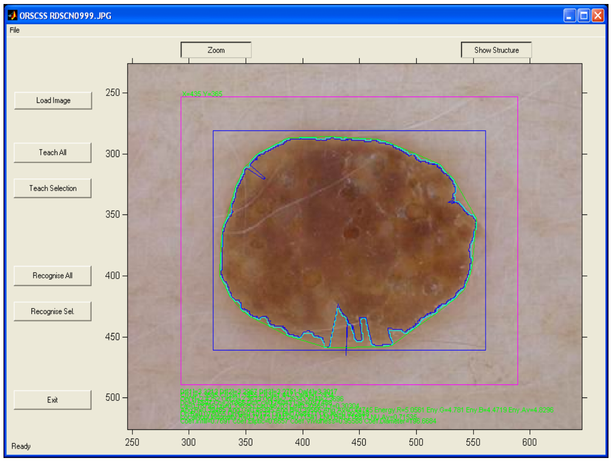

Fig. 2. Example of object segmentation applied to a skin cancer screening system.

IV. Detour Over an Object Contour: Contour Tracing Algorithm

After application of the segmentation algorithm described in the previous section and subsequent binarisation, the two dimensional (binary) representation of the object is the index map $f_{\text{bin}}[m,n]$. This map has the same dimensions as the initial image $f[m,n] \equiv f_{m,n}$ where '1' corresponds to the object and '0' corresponds to the background image. It is then necessary to generate a serial list of boundary coordinates associated with the edge in which the inscribed object is set. Here, we use a novel detour algorithm on an object contour to derive this list of coordinates. The algorithm is both efficient and accurate and is profile independent when compared to other published algorithms, e.g. [13].

Consider the image in Figure 3. The start point (point 'A' in Figure 3) is not significant and, if necessary, can be determined from previous processing stages. For simplicity,

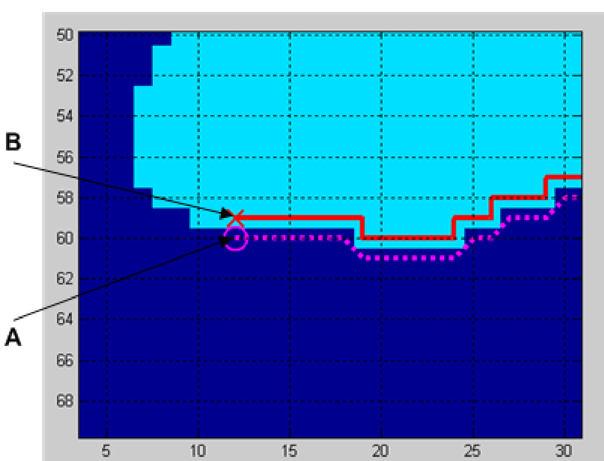

Fig. 3. Detour along an object contour

let the detour algorithm for evaluating an objects contour be named 'Sprocket wheel' because this virtual sprocket is rolled on to a virtual contour. Let us now zoom in on the image and observe how this sprocket wheel looks together with the binary map of an object as in Figure 4. We take the minimum radius of the wheel equivalent to the distance between two points on the image corresponding to a surface consisting of 3×3 elements. Let point 'A' correspond to a wheel axle, with the dashed-line curve, as given in Figure 3, showing its track. One of the points of the wheel will be connected to the objects edge at point 'B' (Figure 3). From the initial conditions, the coordinates of arbitrary points 'A' and 'B' are known. These coordinates can be recovered from preliminary processing or can be found by scanning for the nearest transition from 0 to 1. Thus, the coordinate of a point 0 will correspond to the coordinate of a point 'A', and 1 according to a point 'B'. The

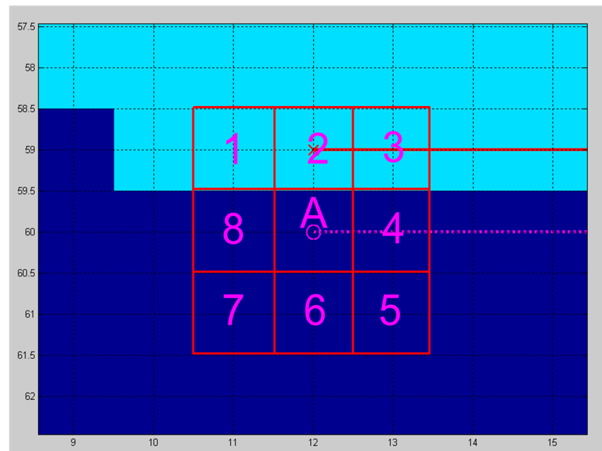

Fig. 4. Structure of a sprocket wheel

direction of movement has no value in the example above and so we consider a counter-clockwise motion. The motion of the virtual sprocket continues along the boundary with the current position of the axis conforming to the initial conditions. For simplicity, we assume that the object does not involve the image boundary. The C++ code for this algorithm is given in Figure 5 which computes the list of coordinates of the edge points of the segmented and binarised object. An example of implementing this algorithm is given in Figure 6 for the object given in Figure 9. The red line of connected points in the figure shows the edge of the object. With reference to the C++ code given in Figure 5, the coordinate data are contained in arrays $ListDotsX[0...ks]$ and $ListDotsY[0...ks]$ for X and Y, respectively.

The advantage of this algorithm over conventional edge detection techniques is that the system considers not only the brightness gradient but also the spatial distribution in terms of the object as a whole. The benefit of this approach is that the movement of axial coordinates occurs less often than the change of edge points and therefore, the computational costs are reduced on average by a factor 2-3 and depend only on the complexity of the object.

The contour generating algorithm described above, whose details are compounded in the C++ code given, is of value in determining the edges of a binarised image. However, in the application considered in this paper, it is applied to produce a contour signal whose fractal properties are used to compute one of a number of features which are discussed later.

Fig. 5. C++ algorithm for contour generation (object edge recognition)

```
int ks=0;
ListDotsX[0]=StartX;
ListDotsY[0]=StartY;
long DotX[9]={0,-1,0,1,1,1,0,-1,-1};//Extend surface of
long DotY[9]={0,-1,-1,-1,0,1,1,1,0};//wheel from axle.
int Ox=StartX;// Set position of points 'A' and 'B'.
int Oy=StartY+1;
int ht,HaveToch=2;
do {  // Cycle while not returning to initial coordinates.
  for (nl=1;nl<=7;nl++){ // Cycle surface of wheel.
    ht=HaveToch+nl;
    if (ht>8) ht=ht-8;
    x1=Ox+DotX[ht]; //Calculate coordinates for
    y1=Oy+DotY[ht]; //surface of the wheel.
    if (*(pp + x1*h + y1)==0){ //If 0 then move the wheel
      Ox=x1; // axle and calculate the point of tangency
      Oy=y1; // of surface with object edge.
      if((ht==1)||(ht==3)||(ht==5)||(ht==7)) HaveToch=ht+5;
      if((ht==2)||(ht==4)||(ht==6)||(ht==8)) HaveToch=ht+6;
      if (HaveToch>8) HaveToch=HaveToch-8;
      break;
    }
    if (*(pp + x1*h + y1)==1){ //If 1 then check the
      if ((x1==StartX)&&(y1==StartY)) break;// initial
      ks=ks++;//conditions
      ListDotsX[ks]=x1;// and save the edge
      ListDotsY[ks]=y1;// coordinate of the object.
    }
  }
} while ((x1!=StartX)||(y1!=StartY));
```

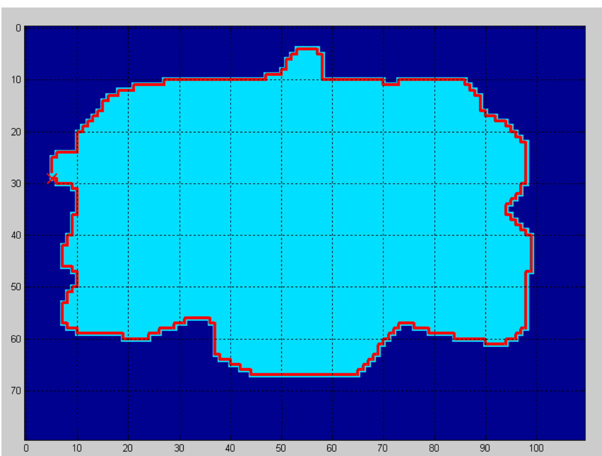

Fig. 6. Result generated by the Contour Walk Algorithm

V. Convex Hull Algorithm: 'Spider'

We now consider the task of obtaining the coordinates of a convex polygon for a binarised image. The binary image has been selected for explanatory purposes only. However, in general, this algorithm can be used as a segmentation procedure for image recognition. This task is given in the MathWorks MATLAB function 'Qhull'. However, the algorithm designed for this application differs from that available in MATLAB in terms of its simplicity, reliability and computational speed. The reason for this is that the number of cycles performed is limited and equal only to the total border length of the object.

The main idea can be thought of in terms of a 'Spider' walking over a contour and pulling a thread behind it. This thread is attached to the object. At the 'point of curvature', the thread stores the coordinates of the outer polygonal point. Thus, the path of the perimeter around the object provides the coordinates of all the outer polygonal points as illustrated in Figure 7. For the initial conditions, we select a position of

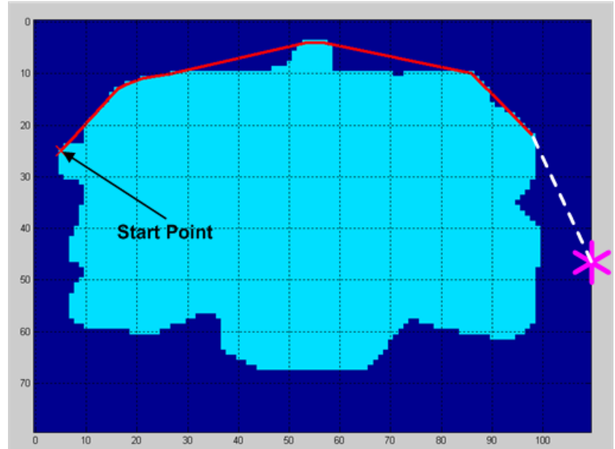

Fig. 7. Coordinate determination for a Convex Hull

Fig. 8. C++ algorithm for Convex Hull

```
{NListDotsX[02*((maxX-minX)+(maxY-minY))] //Create dot list
 NListDotsY[02*((maxX-minX)+(maxY-minY))]}//of bound object.
ListDotsX[0]=StartX; // Set the initial coordinates
ListDotsY[0]=StartY; // for end of thread.
int nc=0,x4,y4,Mx4,My4;
double fi,cs,sn,step,r,RR,bz,sz;
for(nt=0;nt<(2*((maxX-minX)+(maxY-minY)));nt++){//Begin walk
  fi=atan2(NListDotsY[nt]-StartY,...          // around object.
  NListDotsX[nt]-StartX);
    RR=sqrt(pow((NListDotsX[nt]-StartX),2)+...
                            +pow((NListDotsY[nt]-StartY),2));
    cs=cos(fi);
    sn=sin(fi);
    if (fabs(sn)>fabs(cs)){ //Calculate the step length.
      bz=fabs(sn);
      sz=fabs(cs);
    }else{
      bz=fabs(cs);
      sz=fabs(sn);
    }
    step=sqrt(pow(((sz*(1-bz))/bz),2)+pow((1-bz),2))+1;
    for (r=0;r<=RR;r+=step){ // Search for all objects
      x4=round((double)StartX + r*cs);//in line of thread.
      y4=round((double)StartY + r*sn);
      if (*(ppg + x4*h + y4) == 1){
        Mx4=x4; // Save last coordinate
        My4=y4; // in temporary variables.
      }
    }
    if (((Mx4!=StartX)&&(My4!=StartY)) || //Last dot check.
 ((Mx4==StartX)&&(Mx4==NListDotsX[nt])&&(Mx4!=NListDotsX[nt+1]))||
 ((My4==StartY)&&(My4==NListDotsY[nt])&&(My4!=NListDotsY[nt+1]))){
      StartX=Mx4; // Assign new start coordinates.
      StartY=My4;
      nc=nc++;
      ListDotsX[nc]=StartX; // Save list of coordinates
      ListDotsY[nc]=StartY; // for polygon.
    }
}
```

a thread. Clearly, this will be along one of the four image boundaries. The direction of a detour and the selection of the initial conditions does not depend on these conditions. In the example considered here, the detour is clockwise and starts along the left vertical boundary of the image. The C++ code for this algorithm is given in Figure 8.

This algorithm is also useful for defining the geometric location of separated points or objects and can be applied to the development of computer recognition systems, in general. An example of computing this type of polygon for the object is given in Figure 9, the output being represented by the green line. The convex hull algorithm provides information on the basic geometry of the object which yields information on

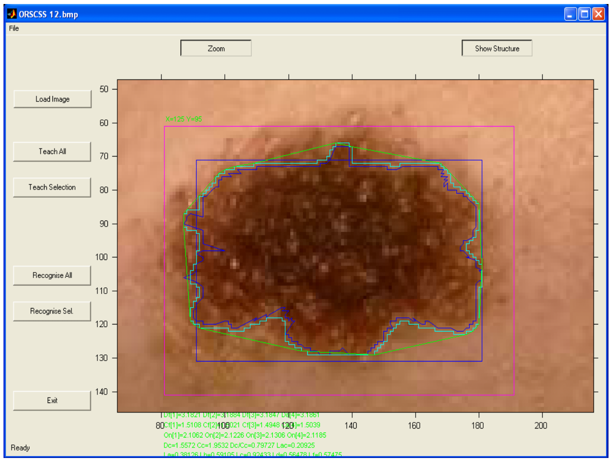

Fig. 9. Object with Contour and Convex Hull

the boundary area, the perimeter and so on. These Euclidean metrics are used to derive features which are discussed in the following section.

VI. 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 (Figure 1). 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 different 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 in the design. The system considered here has been developed to include features associated with the texture of an object, features that are compounded in certain parameters associated with the field of fractal geometry. Texture is particularly important in medical image classification and of primary importance in the application (skin cancer screening) considered in this paper. The following features and their derivatives have been considered (primarily through numerical experimentation) 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 compounded in the following result:

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

where N is the number of pixels defining an object of compact support S 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 center coordinates (m',n') correspond to the local maximums of $\tilde{f}_{m,n}$ within the cluster. The cluster gradient is the average of object gradients,

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

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

Colour Composites Υ and Υ^D

characterise the relationship between the 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 $\upsilon^D = r(a,b,c)$ 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 $q = 4 - D$ [1], [2]. It represents a measure of texture [14] and describes a random fractal image with a power spectrum of the form

$$P^2(k_x,k_y) = c|k|^{-2q},$$

where $|k| = \sqrt{k_x^2 + k_y^2}$ is the spatial frequency and c is a constant. Both q and c can be computed using a least squares method [14].

Lacunarity (Gap Dimension) Λ_k

characterizes the way the ‘gaps’ are distributed in an image [2], [14]. The gap dimension is, roughly speaking, a measure of the number of light or dark regions in an image. It is defined for a 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.

Symmetry Features S_n and M

are estimated by morphological analysis in a 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 of 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:

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

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

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

Geometrical Features
: include the minimum $R_{\min}$ and maximum $R_{\max}$ radius of the object (or ratio $R_{\max}/R_{\min}$), 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 present solution detects objects by computer analysis using mixed mode features that are based on Euclidean and fractal 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 the supervised training system with a number of model objects as described in the following section.

VII. Object Recognition

In order to characterize an object, the 'system' has to know its mathematical representation. Here, this representation is based on the features considered in the previous section which are used to create an image of the object in the 'electronic mind'. This includes the textural features (Fractal Dimension and Lacunarity) for the object coupled with the Euclidean and morphological measures defined. In the case of a general application, all objects are represented by a list of parameters for implementation of supervised learning - Section VII(B) - in which a fuzzy logic system automatically adjusts the weight coefficients for the input feature set.

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 10 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 [9], [10], [11], [12] based on all, or a selection, of the features defined and discussed in Section VI which are combined to produce a feature vector $\mathbf{x}$.

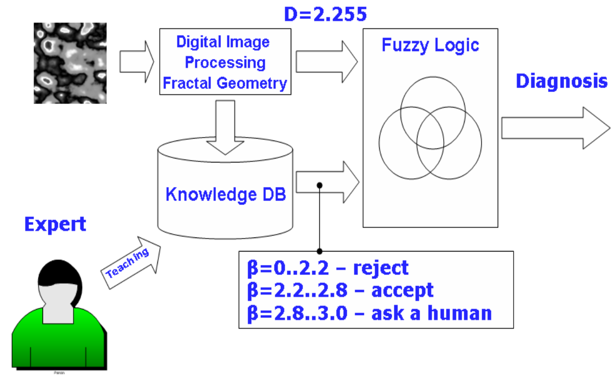

Fig. 10. Basic architecture of the diagnostic system based on the Fractal Dimension D (a single feature) and decision making criteria β.

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 a knowledge database. If $m_j(\mathbf{x})$ is a membership function, then the probability for each j^{th} class and i^{th} feature is given by

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

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 $\mathbf{w}_j$ is the weight coefficient matrix. This value is used to select the class associated with

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

providing a result for a decision associated with 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. The Graphical User Interface (GUI) designed for the training procedure is shown in Figure 13. During this procedure, the system computes and transfers to a knowledge database, a vector $\mathbf{x} = \{x_i\}$, 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.

VIII. 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 features defined in Section VI given the fast algorithms discussed in Sections IV and V.

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. In general, the accuracy of the method will always be lower, than, for example, classical correlative techniques. This is primarily due to padding, when errors can occur during the extraction of a parameter set. However, by using precise parametrisation structures based on the features defined in Section VI, 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 vision 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 or with respect to background for which the method considered can 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 results.

The original approach to the decision process proposed includes the following important steps: (i) the 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 Sections IV and V efficiently select only those objects required; (iv) computation of fractal parameters, in particular, the 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 'tool-kit' 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 skin cancer screening system. Other applications that have been considered to date include a surface inspection system for quality control in the manufacture of steel, details of which will be considered in a future publication.

IX. Application to Skin Cancer Screening: ORSCSS

In this section, we describe the basis and operational performance associated with the Oxford Recognition Skin Cancer Screen System (ORSCSS) developed by Oxford Recognition Limited (ORL) in collaboration with Loughborough University.

Malignant Melanomas are increasingly common and a potentially fatal form of skin cancer, the incidence of which is increasing at a rate greater than any other form of cancer. It is often difficult to visually differentiate a normal mole from abnormal and general practitioners do not usually have significant expertise to diagnose skin cancers. Skin cancer specialists can improve the identification rate by over 80% but are often severely overloaded by referrals from regional general practices. It is possible for a general practitioner to take a high quality digital image of the suspect region on a patients skin and email the result to a remote diagnosis center. However, this can also lead to a (remote) overload and it is for this reason that the system discussed here has been considered in response to developing a screening method that can 'filter' benign melanomas in a general practice.

The system developed has been designed for use with a standard PC with input from a good quality digital camera using Commercial Off-The Shelf hardware. It analyses the structure of a mole or other skin 'defects', detects cancer-identifying features, makes a decision using a knowledge database and outputs a result. Skin cancer experts create a knowledge database by training the system using a number of case-study images. This produces a KDB which 'improves' with the use of the system.

The current system is composed of the following basic steps:

1) Filtering
   The image is Wiener filtered [2] to reduce noise and remove unnecessary and obtrusive features such as light flecks.
2) Segmentation
   The image is segmented to perform a separate analysis of each object (moles and/or other skin features). Two segmentation modes are available:
   - Automatic Mode
     The software identifies a mole as the largest and darkest object in the image. This mode is applicable in most cases.
   - Manual Mode
     The area of interest is manually selected by the user. This is most useful in cases when multiple moles and/or foreign objects are present in the image with possible overlapping features, for example.
3) Feature Detection
   For each object, a set of recognition features are computed based on those discussed in Section VI. The features are numeric parameters that describe the object in terms of a variety of Euclidean and fractal geometries and statistical features in one- and two-dimensions. The one-dimensional features correspond to the border of a mole and the two-dimensional features relate to the surface within the object boundary. In addition, a recognition algorithm is used to analyse the mole *structure* as illustrated in Figure 11. This provides information on the possible growth of the object when an inspection is undertaken over a period of time.
4) Decision Making
   The system uses fuzzy logic to combine features into a decision. A decision is the estimated class of the object and its accuracy. In this particular application, the output is designed to give two classes: *normal* and *abnormal*. This provides the simplest output with regard to the use of the system in a general practice in which abnormal cases are immediately referred to a specialist.

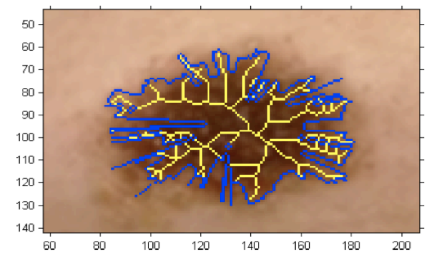

Fig. 11. Analysis of the structure of a mole for comparative growth analysis.

A. Key Advantages

The technology delivers high accuracy and automation which has been made possible by the following innovations:

Fractal analysis
: Biological structures (such as body tissues) have natural fractal properties. Numeric measurements of these properties enables 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 single result.

Advanced fuzzy logic engine
: The knowledge-based recognition scheme used enables highly accurate diagnosis and offers significant improvements over current diagnostic methods.

B. Knowledge Database

ORSCSS is a knowledge-based system and requires extensive training before clinical operation. The training process includes a review and probabilistic classification of appropriate images by experts who can input results using the interface shown in Figure 13. The minimal number of training images depends on the number of classes and the diversity of objects within each class. An analysis and estimation of the number of (normal and abnormal) training images required is given in Section IX(H). The following sections describe how this application can be downloaded, installed and implemented. The demo version, which has been made available for this publication, includes documentation which is itemised in the following sections.

C. Platform Requirements

System Requirements

- Windows 98/ME/2000/XP
- CD-ROM Drive
- 256 MB RAM
- 30 MB hard disk space

Image Requirements

- Input format: JPEG, BMP or TIF
- Image size: 640x480 to 1024x728
  (higher image resolution requires RAM of 512 Mb and more)
- Good focus with no motion blur
- Uniform lighting
- Capture of the object which is well centred in the image frame and does not, for example, extend beyond the image boundaries

D. Installation

1) The downloadable demo version of ORSCSS is available from hppt://www.oxreco.com/setup.zip.
2) Installation is initiated through `setup.exe` from the root folder in which the downloaded application has been placed (after unzipping the downloaded file setup.zip).
3) Follow the instructions on screen.

E. Recognition Mode

1) Click **Load Image** and select an image of a mole or other skin 'defect'. Samples can be found in folder `Pictures`, which, by default, reside in

   `...\ORSCSS␣Demo\Pictures\`.

2) Click **Recognise All**. If the object(s) is not located automatically, then click **Recognise Selection** and select the area of interest.
3) Recognition and class estimation takes approximately 20 seconds (for a typical modern PC operating under an XP windows environment) producing an output of the type given in (Figure 12).

F. Teaching

1) The default knowledge database is loaded from

   `...\ORSCSS␣Demo\bin\def.kdb`.

   To create a new database, select **New knowledge DB** from the **File** menu (see Figure 14).
2) Click **Load Image** and select a picture of a mole, for example.
3) Click **Teach All**. If the mole is not found automatically click **Teach Selection** and select the area of interest.
4) ORSCSS analyses the mole for 10-30 seconds whereupon the Teaching Dialog (Figure 13) pops up. Enter your estimation:
   a) Class: number 1 (for Abnormal) or 2 (for Normal),
   b) Probability: a number between 0.0 and 1.0. 1.0 means you are absolutely sure, whereas zero should not normally be used. Typical values are 0.90-0.95.
5) Repeat Steps 1-4 above to process all training images.
6) Select **Save knowledge DB...** from **File** (see Figure 14) and enter a file name for the knowledge database.

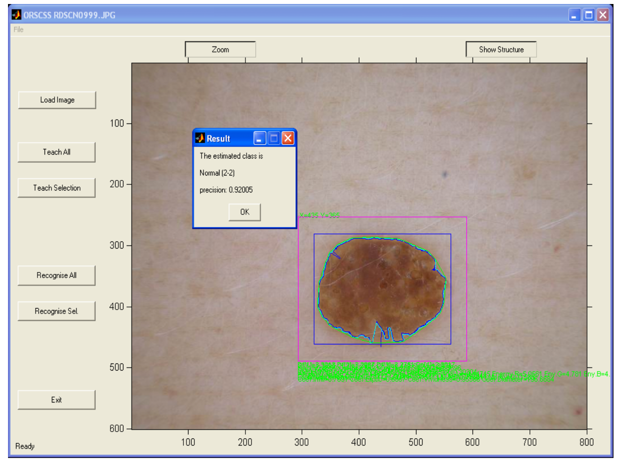

Fig. 12. Recognition result

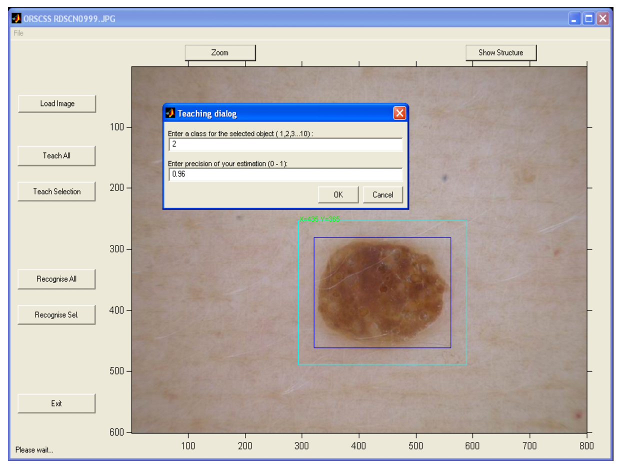

Fig. 13. Teaching dialog

G. User Interface

Main Window

The commands available from the main window (see Figure 2) are summarised in Table 1.

File Menu

The file menu is given in Figure 14 whose menu items and actions are summarised in Table II.

Command Line Execution

To launch the system in automatic mode type:

`ORSCSS.exe␣"LoadGraf"␣%1`

where `%1` is an image name (JPEG, BMP or TIFF formats are supported).

H. Estimation of the Minimal Number of Samples

There are approximately 65,000 new cases of skin cancer each year in the UK, which is about 5% of the total number of patients examined annually [15]. Let p be the probability of unrecognized cases. Then $q = 1 - p$ is the probability of recognized cases and the number of mistakes is determined by $S_n^k = C_n^k p^k q^{n-k}$ where n is number of experiments, k is the number of misidentifications and $C_n^k = \frac{n!}{k!(n-k)!}$.

Button	Action
Load Image	loads image in JPEG, BMP or TIF formats
Teach All	performs teaching in automatic mode
Teach Selection	performs teaching in manual mode
Recognise All	performs recognition in automatic mode
Recognise Selection	performs recognition in manual mode
Exit	closes the application
Zoom	switches on/off the zoom mode (use the left mouse button to zoom in and the right button to zoom out)
Show Structure	displays the mole boundary and features for growth analysis

TABLE I

BUTTONS AND ASSOCIATED ACTIONS ON THE MAIN WINDOW OF ORSCSS.

Menu Item	Action
New knowledge DB	resets knowledge database
Open knowledge DB...	loads knowledge database from a kdb file)
Save knowledge DB...	saves knowledge database to a kdb file
Open Image...	loads image in JPEG, BMP or TIF formats
Exit	closes the application

TABLE II

MENU ITEMS AND ASSOCIATED ACTIONS OF ORSCSS FILE MENU.

Our problem is to compute the number of images (tests) n required to estimate the error probability within the range $\pm 1\%$ (0.01) and degree of confidence $\alpha = 0.99$. Assuming the error is normally distributed with a standard deviation of σ, the probability of estimating the sampling fraction w within a degree of confidence Δ is defined by

$$P(|w - p| \leq \Delta) = \Phi(t),$$

where

$$\Phi(t) = \frac{2}{\sqrt{2\pi}} \int_0^t e^{-x^2/2} dx,$$

p is the probability of the error and $t = \Delta/\sigma$. Suppose we find p for 0.01 and let p' be the real probability. Setting the

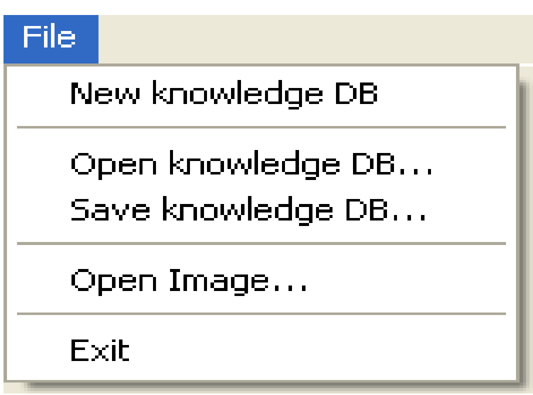

Fig. 14. File menu

confidence interval at $\alpha = 0.99$, our minimal error is

$$P\left(|p' - p| < 0.01\right)$$

so that

$$P\left(|S_k^n - pn| 0.01n\right) < \alpha$$

which, by the law of large numbers yields

$$0.01 \frac{\sqrt{n}}{\sqrt{pq}} \geq 2.58$$

or

$$\sqrt{n} \geq 2580\sqrt{pq}$$

For all p, $pq \leq 1/4 \Rightarrow n \geq 16641$ and if $p < 0.1$ then $q > 0.9$ and $pq < 0.1$. We can then evaluate the minimal requirement n, i.e.

$$n \geq 6656$$

However, in practice, this number may not be enough to assess the accuracy of the recognition system due to the following reasons: (i) the assumption that p and w are constant for all types of moles is very doubtful and it is necessary to carry tests with a variety of skin defects; (ii) the recognition quality will significantly vary in time during the test process since the knowledge database is constantly updated. Nevertheless, the value of n given here provides an order of magnitude of the number of images required to train the system effectively.

I. Comparison with other approaches

There are a number of commercially available products which offer a range of aids and tools for skin cancer detection. Some of them use an extensive database to estimate the pathology and may require a relatively significant amount of time to make a decision. Other products calculate several properties and represent them graphically. Medical staff are then used to make a final decision. More interesting techniques involve the capture of images using different sensors or a multiplicity of different images. However, these systems are as yet, not approved for clinical diagnosis and are not a referenced form of dermatoscopy. The following list provides some of the more common products in the field: (i) MoleMAX - http://www.molechecks.com.au; (ii) DermLite - http://www.dermlite.com/mmfoto.html; (iii) DermoGenius Lite - http://www.dermogenius.de; (iv) MelaFind - www.melafind.com. Comparing these products with the methods developed for this paper, it is clear that there are no other automatic recognition systems with self-adjusting procedures and self-controlled functions. The tests undertaken to date, have established the capacity for ORSCSS to be used in routine clinical conditions provided extensive training of the system has been undertaken.

X. 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 work reported in this paper is part of a wider investigation into the numerous applications of pattern recognition using fractal geometry as a central processing kernel. This has led to the design of a new library of pattern recognition algorithms including the computation of parameters in addition to those that have been reported here such as the information dimension, correlation dimension and multi-fractals [14]. The inclusion or otherwise of such parameters in terms of improving vision systems such as the one considered here remains to be understood. However, from the work undertaken to date, it is clear that texture based analysis alone is not sufficient in order to design a recognition and classification system. Both Euclidean and fractal parameters need to be combined into a feature vector in order to develop an operational vision system which includes objects that have textural properties such as those associated with medical imaging.

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. 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 (ANN). 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.

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