Dahlem Workshop Reports

verlag chemie

Life Sciences Research Report 15

Biomedical Pattern Recognition and Image Processing

Dahlem Workshop Report on
"Biomedical Pattern Recognition and Image Processing"
held in Berlin in May, 1979.

Editors: K. S. Fu and T. Pavlidis

The use of computers for the processing of biomedical data is growing while it faces a number of challenging questions. A group of specialists in pattern recognition, signal processing, computers and the biomedical sciences examine here the applicability of general pattern recognition and image processing methods to specific biomedical problems. This volume presents their views and suggestions for the development of the field.

1979. 443 pages with 76 figures and 7 tables.
Softcover. DM 54,—. ISBN 3-527-12017-3

Fields of interest:
Biochemistry, Biology, Biophysics, Genetics, Microbiology, Oceanography, Botany.

Biomedical Pattern Recognition and Image Processing, eds. K.S. Fu and T. Pavlidis, pp. 153-178. Berlin: Dahlem Konferenzen 1979. Verlag Chemie GmbH, D-6940 Weinheim.

Texture Analysis for Biomedical Imagery [1]

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Abstract. Statistical, structural, and hybrid techniques for optical texture analysis are reviewed. Statistical techniques are categorized further into four approaches: orthogonal transformations, Markovian analysis, mathematical morphology, and gradient analysis. Biomedical images of microscopic and macroscopic structures possess biologically relevant and clinically diagnostic textural information. Techniques discussed in this paper may be appropriate in pathology, hematology, immunology, genetics, radiology, and nuclear medicine.

INTRODUCTION

The systematic analysis of visual textures began with the realization that texture perception is the means by which humans detect the presence and character of a visual surface. Once the concept of texture was formulated, visual scenes were interpreted on the basis of their textural content. Visual scenes were decomposed into sets of uniform visual textures, gradual changes in these textures, and textural discontinuities. Perception experiments then led to descriptive definitions of textures (45,73).

Quantitative measures of textural information became available with the advent of automatic image analysis technology (3,33,35, 56,77,96). The instrumentation required to implement optical tex-analysis is well described in the literature (63,115) and is not the subject of this paper.

[1] This work was supported in part by a William Penn Foundation Grant to The Johns Hopkins University.

Although optical texture analysis may require complex and expensive machines, it may be appropriate for some routine tasks (e.g., enumeration of metaphase spreads), quantitative tasks (e.g., computation of a nuclear chromatin coarseness index), and complex tasks (e.g., detection of histological changes associated with alterations to the biochemical environments of tissues) (62). Automated analysis of biomedical image textures has already been applied to a wide variety of biomedical research problems (52,81). Images of both microscopic and macroscopic structures have been the subject of these research projects.

The following sections define and survey current approaches to computerized optical texture analysis. They also illustrate the application of these techniques to (a) microscopic structure analysis in pathology, hematology, immunology, and cytogenetics, and (b) macroscopic structure analysis in radiology and nuclear medicine. The abundant literature concerned with perception theory, psychophysics of visual textures (see Cooper et al., this volume, (14)) and texture modeling and synthesis is significant although it is beyond the scope of the work discussed in this review paper.

APPROACHES TO OPTICAL TEXTURE ANALYSIS

The advent of automatic image analysis resulted in two fundamentally different approaches to optical texture analysis, the statistical and the structural. The statistical approach generates parameters to characterize the stochastic properties of the spatial distribution of gray levels in an image. The structural approach is used to analyze visual scenes in terms of the organization and relationships among its substructures. There is a need to classify alternative approaches to texture characterization because no general theory yet exists. A survey of the representative literature regarding optical texture analysis is presented below and organized according to the statistical, structural, and hybrid approaches. A thorough review of texture models and approaches has been presented by Haralick with illustrations (35).

Statistical

Orthogonal transformations. Spatial frequency characteristics of two-dimensional images can be expressed by the autocorrelation function or by the power spectra of those images. Both may be calculated digitally and/or implemented in a real-time optical system.

Kaizer (46) assumed a circularly symmetric autocorrelation function ρ, and computed, for each image, the distance d such that $P(d) = \rho^{-1}$. Subjects ranked images from fine to coarse in this study and determined a correlation of 0.99 between the subject rankings and the distance d. These results indicate that the fineness or coarseness property of textures is related to the autocorrelation function.

Lendaris and Stanley (53,54) used optical techniques to perform texture analysis on a data base of low altitude photographs. They illuminated small circular sections of those images and used the Fraunhoffer diffraction pattern to generate features for identifying photographic regions. The major discriminations of concern to these investigators were those of man-made versus natural scenes. The man-made category was further subdivided into roads, intersections of roads, buildings, and orchards.

Feature vectors extracted from these diffraction patterns consisted of forty components. Twenty of the components were mean energy levels in concentric annular rings of the diffraction pattern, and the other twenty components were mean energy levels in 9°-wedges of the diffraction pattern. Greater than 90% classification accuracy was reported using this technique.

Cutrona, Leith, Palermo, and Porcello (19) present a review of optical processing methods for computing the Fourier transform. Goodman (29), Preston (80), and Shulman (94) also present in their books comprehensive reviews of Fourier optics. Swanlund (100) discusses the hardware specifications for a system using optical techniques to perform texture analysis.

Gramenopolous (30) used a digital Fourier transform technique to analyze aerial images. He examined subimages of 32 x 32 pixels and determined that for an (ERTS) image over Phoenix, spatial frequencies between 3.5 and 5.9 cycles/km contained most of the information required to discriminate among terrain types. An overall classification accuracy of 87% was achieved using image categories of clouds, water, desert, farms, mountain, urban, river bed, and cloud shadows. Horning and Smith (41) used a similar approach to interpret aerial multispectral scanner imagery.

Bajscy (5,6) and Bajscy and Lieberman (7,8) computed the two-dimensional power spectra of a matrix of square image windows. They expressed the power spectrum in a polar coordinate system of radius (r) versus angle (a). As expected, they determined that directional textures tend to have peaks in the power spectrum along a line orthogonal to the principle direction of the texture. Blob-like textures tend to have peaks in the power spectrum at radii (r) comparable to the sizes of the blobs. This work also shows that texture gradients can be measured by determining the trends of relative maxima of radii (r) and angles (a) as a function of the position of the image window whose power spectrum is being analyzed. For example, if the power peaks along the radial direction tend to shift towards larger values of r, the image surface is more finely textured.

In general, features based on Fourier power spectra have been shown to perform more poorly than features based on second order gray level statistics (see Markovian analysis) or those based on first order statistics of gray level differences (see Gradient analysis) (113). Presence of aperture effects has been hypothesized to account for part of the unfavorable performance by Fourier features compared to space-domain gray level statistics (22), although experimental results indicate that this effect, if present, is minimal.

Transforms other than the Fourier transform can be used for texture analysis. Kirvida (47) compared the fast Fourier,

Hadamard, and Slant transforms for textural features on aerial images of Minnesota. Five classes (i.e., hardwood trees, conifers, open space, city, and water) were studied using 8 x 8 subimages. A 74% correct classification rate was obtained using only spectral information. This rate increased to 98.5% when textural information was also included in the analysis. These researchers reported no significant difference in the classification accuracy as a function of which transform was employed.

Pratt (75) and Pratt, Faugeras, and Gagalowitz (76) suggest measuring texture by the coefficients of the linear filter required to decorrelate an image and by the first four moments of the gray level distribution of the decorrelated image. They have shown promising preliminary results.

The linear dependence which one image pixel has on another is well-known and can be measured by the autocorrelation function. This linear dependence is exploited by the autoregression texture characterization and synthesis model developed by McCormick and Jayaramamurthy (60) to synthesize textures. McCormick and Jayaramamurthy used the Box and Jenkins (13) time series seasonal analysis method to estimate the parameters of a given texture. These estimated parameters and a given set of starting values were then used to illustrate that the synthesized texture was close in appearance to the given texture. Deguchi and Morishita (21), Tou, Kao, and Chang (107), and Tou and Chang (105) used similar techniques.

The autoregressive model for texture synthesis begins with a randomly generated noise image. Then, given any sequence of K synthesized gray level values in its immediately past neighborhood, the next gray level value can be synthesized as a linear combination of those values plus a linear combination of the previous L random noise values. The coefficients of these linear combinations are the parameters of the model. Texture analysis work based on this model requires the identification of these coefficient values from a given texture image.

Markovian analysis. Textural features can also be calculated from a gray level spatial cooccurrence matrix. Markovian analysis[2] uses such matrices to characterize the probabilistic relationships among the gray levels of neighboring[3] pixels. The cooccurrence matrix of an image I is defined as follows. Suppose that the integer image intensities lie in the range $[0,M-1]$. Then the value of the $(i,j)^{th}$ position, $G(i,j)$, of the M x M cooccurrence matrix is the number of pairs of neighboring resolution cells (pixels) having gray levels i and j, respectively. The cooccurrence matrix can be normalized by dividing each entry by the sum of all of the entries in the matrix. Conditional probability matrices can also be used for textural feature extraction with the advantage that these matrices are not affected by changes in the gray level histogram of an image, only by changes in the topological relationships of gray levels within the image.

Apparently Julesz (44) was the first to use cooccurrence statistics in visual human texture discrimination experiments. Darling and Joseph (20) used statistics obtained from nearest-neighbor gray-level transition probability matrices to measure texture using spatial intensity dependence in satellite images. Bartels and Wied (11), Bartels, Bahr, and Wied (10) and Wied, Bahr, and Bartels (114) used one-dimensional cooccurrence statistics for the analysis of cervical cells. Rosenfeld and Troy (89), Haralick (33) and Haralick, Shanmugan, and Dinstein (38) suggested the use of spatial dependence matrices for arbitrary distances and directions. Galloway (27) used gray level run length statistics to measure texture. These statistics are computable from cooccurrence matrices assuming that an image was generated by a Markov process. Chen and Pavlidis (16) used the cooccurrence

[2] Markovian analysis is a term which refers to use of statistical estimates of gray-level spatial dependencies to characterize textured images. The term does not imply the existence of a well-defined underlying statistical process although this technique has been applied to image data generated by Markov processes.

[3] Neighboring pixels are not necessarily defined as only the four or eight closest neighbors.

matrix in conjunction with a split and merge algorithm to segment an image at textural boundaries. Tou and Chang (106) used statistics from the cooccurrence matrix, followed by a principal components eigen vector dimensionality reduction scheme (Karhunen-Loeve expansion) to reduce the dimensionality of the classification problems.

Statistics which Haralick, Shanmugan, and Dinstein (38) computed from such cooccurrence matrices have been used to analyze textures in satellite images (37). An 89% classification accuracy was obtained. Additional applications of this technique include the analysis of microscopic images (36), pulmonary radiographs (17), and cervical cell, leukocyte, and lymph node tissue section images (78,79).

Haralick (34) illustrates a way to use cooccurrence matrices to generate an image in which the value at each resolution cell is a measure of the texture in the resolution cell's neighborhood. All of these studies produced reasonable results on different textures. Connors and Harlow (18) concluded that this spatial gray level dependence technique is more powerful than spatial frequency (power spectra), gray level difference (gradient), and gray level run length methods (27) of texture quantitation.

McCormick and Jayaramamurthy (61) and Read and Jayaramamurthy (84) analyze and synthesize textures using optimum sets of gray level strings ("interval covering approach"). This memory-intensive technique is not appropriate for images with a large number of gray levels.

Mathematical morphology. A structural element and filtering approach to texture analysis of binary images was proposed by Matheron (58) and Serra and Verchery (93). This approach requires the definition of a structural element (i.e., a set of pixels constituting a specific shape such as a line or square) and the generation of binary images which result from the translation of the structural element through the image and the erosion of image features (i.e., contiguous pixels having the value 1) by the structural element. The textural features can be obtained from the new binary images by counting the number of pixels having the value 1. This mathematical morphology approach of Serra and Matheron is the basis of the Leitz Texture Analyser (TAS)(69,70,91). A broad spectrum of applications has been found for this quantitative analysis of microstructures method in materials science and biology. Watson (112) summarizes this approach to texture analysis.

More precisely, let H be defined as a given structural element. The translate of H is referred to as H(i,j). H(i,j) is the translation of all of the pixels of H by the distance x=i, y=j; no rotation or shape distortion occurs. Let F be defined as a binary image object (i.e., blob[4]). Then the erosion of F by the structural element H, written $F\Theta H$, is defined as

$$F\Theta H = \{(m,n) \mid H(m,n) \subseteq F\}.$$

The eroded image J obtained by eroding F with structural element H is a binary image whose pixels take the value 1 for all resolution cells in $F\Theta H$. The number of pixels in image J is proportional to its area. Theoretical properties of the mathematical morphology operator "erosion" are presented by Matheron (59), Serra (92), and Lantuejoul (50).

Textural properties can be obtained from the erosion process by appropriately parameterizing the structural element (H) and determining the number of elements of the erosion as a function of the parameter's value.

Gradient analysis. Rosenfeld and Troy (89) and Rosenfeld and Thurston (88) regard texture in terms of the amount of "edge" per unit image area. An edge can be detected by a variety of local mathematical operators which essentially measure some approximation to the gradient of the image intensity function.

[4] A blob is a set of contiguous pixels with the value 1 in a binary image, exclusively surrounded by pixels with the value 0.

Rosenfeld and Thurston used the Roberts gradient[5] and then computed, as a measure of texture for any image window, the average value of the Roberts gradient taken over all of the pixels in the window. Sutton and Hall (99) extend this concept by measuring the gradient as a function of the distance between pixels. An 80% classification accuracy was achieved by applying this textural measure in a pulmonary disease identification experiment.

Related approaches include Triendl (108) who first smoothed the image using 3 x 3 neighborhoods, then applied a 3 x 3 digital Laplacian operator, and finally smoothed the image with an 11 x 11 window. The resulting texture parameters obtained from the frequency filtered image were used as a discriminatory textural feature. Hsu (42) determined edgeness by computing gradient-based measures for the intensities in a neighborhood of pixels. The deviation of the intensities in the neighborhood from both the intensity of the central pixel and from the average intensity of the neighborhood was computed. The histogram of a gradient image was used to generate textural parameters by Landeweerd and Gelsema (49) to measure texture properties in the nuclei of leukocytes. Rosenfeld (85) generates an image whose intensity is proportional to the edge per unit area of the original image. This transformed image is then further processed by gradient transformations prior to textural feature extraction.

Many heuristic approaches to texture analysis have been devised and implemented. Frequently these techniques are not well understood and, consequently, they are difficult to classify into one of the four statistical approaches described above. For example, mosaic texture models tessellate a picture into regions and assign a gray level to the region according to a specified probability density function (90). Among the kinds of mosaic models are the Occupancy Model (66), Johnson-Mehl Model (28), Poisson Line Model (65), and Bombing Model (101).

[5] The Roberts gradient is defined as the sum of (a) the magnitude of the difference of the gray values of diagonally neighboring pixels and (b) the magnitude of the difference of the gray values of the neighboring two pixels on the orthogonal diagonal.

The mosaic texture models seem readily adaptable to numerical analysis. Their properties seem amenable to mathematical analysis although their visual interpretation is not as well understood.

Structural

Pure structural models of texture presume that textures consist of primitives which appear in quasi-periodic spatial arrangements. Descriptions of these primitives and their placement rules can be used to describe textures (87). The identification and location of a particular primitive in an image may be probabilistically related to the identification and distribution of primitives in its neighborhood.

Carlucci (15) suggests a texture model using primitives of line segments, open polygons, and closed polygons in which the placement rules are given syntactically in a graph-like language. Zucker (116,117) conceives of a real texture to be the distortion of an ideal texture. The underlying ideal texture may be represented by a regular graph in which each node is connected to its neighbors in an identical fashion. Each node corresponds to a cell in a tessellation of the plane. The underlying ideal texture is transformed by distorting the primitive at each node to make a less periodic and less deterministic texture. Zucker's model is more of a competence based model than a performance model.

Lu and Fu (57) give a tree grammar syntactic approach for texture analysis. They divide a texture into small (compared to the image dimension) square windows (9 x 9). The spatial structure of the pixels in each window is expressed in a tree structure. The assignment of gray values to each pixel is given by the rules of a stochastic tree grammar. Finally, special consideration is given to the placement of windows with respect to each other to preserve the coherence between windows. Lu and Fu illustrate the power of their technique with both texture synthesis and analysis experiments. Tsai and Fu (109) use syntactic techniques and algorithms (e.g., direction detectors, rotational grammars, optimum window size inferrence algorithms) to segment and recognize agricultural area photographs which are markedly textured.

These structural approaches, alternatively referred to as syntactic pattern recognition techniques, have received increasing attention in recent years although most biomedical texture analysis research has concentrated historically on statistical approaches (Fu, this volume). Structural techniques may be appropriate for segmenting complex multitextured biomedical images (e.g., tissue section images), characterizing their quasi-repetitative patterns, and generating synthetic images of similar appearance.

Hybrid

Tsuji and Tomita (110) and Tomita, Yachida, and Tsuji (103) describe a combined statistical/structural approach to texture analysis. First, a scene is segmented into elementary regions based on some gray level spatial distribution property such as uniformity. These regions are operationally defined as the primitives. Associated with each primitive is a list of properties such as size, shape, and color. A frequency histogram of these properties of all primitives in the scene can be produced. If the scene can be decomposed into two or more regions of homogeneous texture, then the histogram will be multimodal. In this case each primitive in the scene can be assigned the appropriate modal value in the histogram. A region growing-cleaning process on the assigned primitive values yields homogeneous textural regions. This technique is appropriate for scene segmentation.

A complete segmentation may not result if populations in the histogram of the primitives' properties are not well separated. In this case, the entire process can be repeated using the homogeneously textured region segments identified earlier. The procedure may not work at all if each of the texture regions consists of mixtures of more than one type of primitive. Resolution of this problem may indicate the use of cooccurrence matrices of primitive properties.

Zucker, Rosenfeld, and Davis (118) used a form of this technique by filtering a scene with a spot detector. Non-maxima pixels on the filtered scene were deleted. If a scene has many different homogeneously textured regions, the histogram of the relative-maximum spot detector filtered scene will be multimodal. Assigning the maxima to their respective modes and region growing-cleaning then produces segmented scenes.

The idea of the constant gray level regions of Tsuji and Tomita or the spots of Zucker can be generalized to regions which are peaks, pits, ridges, ravines, hillsides, passes, breaks, flats, and slopes. (72,104).

Rosenfeld and Troy (89) suggest the number of extrema per unit area as a texture measure. They suggest defining extrema in one dimension (along a horizontal scan line) in the following way: in any row of pixels, a pixel i is a relative minimum (maximum) if its neighboring gray levels do not have smaller (larger) values. Thus, the interior of any constant gray level sequence of pixels is considered simultaneously as a relative minimum and relative maximum, regardless of whether the constant gray level sequence is just a plateau on the way down or on the way up from a relative extremum. Ledley (51) also suggests computing the number of extrema per unit area as a texture measure.

The algorithm employed by Rosenfeld and Troy centers a square window around each relative maxima or minima pixel and counts the number of relative maxima or minima pixels within that window. A texture image is then created to correspond to a defocused image of the number of relative extrema per unit area within these windows.

Mitchell, Myers, and Boyne (68) suggest the extrema idea of Rosenfeld and Troy and additionally propose to use true extrema and to operate on a smoothed image to eliminate extrema due to noise (67). Ehrich and Foith (23,24) use a relational tree to characterize the structure of relative extrema.

Two properties can be associated with every extrema in the one-dimensional case: height and width. The height of a maxima can be defined as the difference between the value of the maxima and the highest adjacent minima. The width of a maxima is the distance between its two adjacent minima. Apostolico, Caianiello, Fischetti, and Vitulano (2) use two-dimensional histograms of such features.

In two dimensions, the relative height of a relative maxima is the difference between its value and that of the highest adjoining relative minima. Its size is defined by the constituent number of pixels in this "mountain range". Its shape can be characterized by features such as elongation, circularity, and symmetry. Elongation can be defined as the ratio of the larger to the smaller eigen value of the 2 x 2 second moment matrix obtained from the (x,y) coordinates of the border pixels (4,25). Circularity can be defined as the ratio of the standard deviation to the mean of the radii from the region's center to its border (34). The symmetric axis feature can be determined by thinning the region down its skeleton and counting the numbers of pixels in the skeleton. The direction of the elongation or the direction of the symmetric axis may also be measured.

Osman and Sauker (71) use the mean and variance of the height of mountains or the depth of valleys as properties of primitives. Tsuji and Tomita (110) use size. Histograms and statistics of histograms of these primitive properties are all potential measures for textures.

Hanson, Riseman, and Nagin (32) have suggested measuring properties of macrotexture by constructing a cooccurrence matrix of primitive versus primitive and using statistics similar to those used in the Markovian analysis.

BIOLOGICAL APPLICATIONS

Coherent optical processing of cervical cytology samples has been performed using a specially designed Fourier spectrum analyzer and a solid state optical detector array (48). The performance of this exfoliative cytology automated screening system protype was disappointing since a 1% false negative and 10% false positive error rate was obtained using atypical samples with a 1% probability of occurrence of malignant cells.

Gray level transition probability matrices have been used in the TICAS program (11) to detect small changes and differences in the chromatin distribution patterns of cells. This Markovian analysis technique enabled the investigators to follow changes in mouse thoracic-duct lymphocytes as a function of exposure to increasing doses of ionizing radiation. Arguments have been presented that this technique may allow one to describe the texture of cell nuclei with a greater sensitivity than available by human perception. Results of other experiments (79) show that Markov parameters achieve high rates of correct classification for cervical cell and lymph-node tissue-section applications and moderate rates for leukocyte discrimination applications. Flow microfluorometric systems have been used successfully to reduce the number of cells which require processing by these computationally intensive algorithms (26). Encouraging results were also achieved using Markovian analysis in a study which correlated computer gradings of cell populations from breast cancers with the subjective morphological gradings from trained human diagnosticians (40).

Many researchers attempt to assess the significance of optical texture analysis in exfoliative cervical cytology (74). Tanaka determined that reliable automatic assessment of cytologic samples requires the measurement of chromatin patterns (102). Gradient analysis techniques were tested on four classes of 200 cervical cells (i.e., basal, metaplastic, dysplastic, and carcinoma in situ) (1). A greater than 90% correct classification rate was obtained using features such as the variance of the histograms of Laplacian filtered images. The authors concluded that texture of the nuclei of Pap-stained cells is a significant discriminatory feature.

Mathematical morphology techniques have also been applied to cervical cytology (64). Results of this work (97) are encouraging although the overall system performance cannot be assessed yet. Commercially available instruments (e.g., Cambridge-IMANCO Quantimet) have successfully used a similar technique to detect and enumerate metaphase spreads for cytogenetic applications.

Tissue section images are complex pictorial scenes, whose decomposition and analysis are some of the most difficult tasks for image analysis due to the presence of diffuse boundaries, three-dimensional structures, non-stoichiometric staining with a large dynamic range of optical densities, huge variations in the sampling and preparation methods, etc. However, the biological and clinical significance of tissues is justification for their study by objective techniques (12,82). In addition, this application may be appropriate to develop syntactic pattern recognition techniques and to test structural and hybrid texture analysis concepts.

Differential leukocyte counting was a major thrust of biomedical image analysis a decade ago (83). The topological arrangement gray levels in cell nuclei was already considered at that time (43). Current research using optical texture analysis to recognize and discriminate among leukocyte classes (31,111) span Markovian analysis, gradient analysis (39), and mathematical morphology (55) statistical techniques. Immunological applications for texture analysis have also been successfully demonstrated such as the discrimination between T and B cell lymphocytes and the further subclassification of T cells by computerized microphotometry (Olsen, Anderson, and Bartels, personal communication, (9)). Notable by its general absence is the application of structural and hybrid approaches to quantitative cytopathology and hematology.

Applications of texture analysis in radiology and nuclear medicine historically include the analysis of patients with pulmonary interstitial disease (e.g., pneumoconiosis) involving abnormalities in the pulmonary blood vessels, lymphatics, and connective tissue (86,95), and the analysis of mammograms (Kimme-Smith, Frankl, and Sklansky, personal communication, (98)). The accompanying rib edge detection problems and point calcification problems may be better resolved by pattern recognition techniques other than texture analysis.

DISCUSSION AND CONCLUSIONS

Optical textures result from the spatial variation of gray levels within images. The quantitative characterization of biomedical image textures may generate biological and clinical information which is useful in performing routine, quantitative and/or complex image analysis tasks by humans or machines. However, the objective and quantitative measurement of image textures is a non-trivial feature extraction problem.

The orthogonal transformation approach is appealing because spatial frequency data may be extracted instantaneously using coherent optical processing systems. Unfortunately, features based on the Fourier power spectra data have resulted in poorer image classification accuracies than features from alternative approaches. In contrast, Markovian parameters result in encouraging rates of correct classification of images although this technique may be computationally intensive. The mathematical morphology approach benefits from the availability of commercial instruments to implement functions and automatically compute texture parameters. However, the sparse distribution of these machines in biomedical research laboratories prevents reviewers from accurately assessing the potential of this technique in biology and medicine. The gradient analysis approach, mathematically similar to Markovian analysis, also yields encouraging results.

Structural and hybrid approaches to texture analysis presume the existence of primitives which appear in quasi-periodic spatial arrangements. They describe the character and placement rules of these primitives. These approaches may be particularly

appropriate for processing (e.g., segmenting) and characterizing complex multitextured scenes although little work has been performed using these techniques on biomedical images in contrast to the use of statistical techniques.

Biomedical applications for texture analysis span many disciplines. Studies in exfoliative cytology, differential leukocyte counting, and T and B cell lymphocyte differentiation are prototypic examples of the use of optical texture analysis to study microscopic structures. Studies in pulmonary radiology and mammography are examples of the use of these techniques to study macroscopic structures.

Imaging techniques in addition to optical microscopy and projection radiography, may warrant the application of computerized optical texture analysis. These new applications include electron microscopy for the interpretation of microscopic structures (e.g., analysis of physical surface properties of cell nuclei) and ultrasonography and tomography for the interpretation of macroscopic structures (e.g., analysis of radionuclide liver images).

Acknowledgements. The authors express their appreciation to M. H. Vansickel for his competent assistance in the literature search and to B.A. Harry for expertly typing this manuscript.

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