AUTOMATED PICTORIAL PATTERN ANALYSIS - PROGRAMMING METHODS

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ABSTRACT

Progress on programming techniques for automated analysis of three-dimensional matrices representing cell clusters is reviewed. Our philosophy for picture processing is based upon the unproved assumption that an empirical relation exists which will allow positive identification of a useful fraction of a given cell type. This means that we are willing to accept a program which will identify only a fraction of the cells, provided such identification is very reliable. At present, we are working with 32 x 32 element matrices containing light intensity values. The picture analysis is carried out by an IBM 360/50. Tested programs include those which will allow for illumination correction, sharpening, intensity contours leading to data representation in a binary matrix form. The methods employed are discussed and illustrated.

TEXT

Microphotographs of stained sections of muscle tissue (Fig. 1) are used as input to a closed-circuit Vidicon TV system. The data acquisition methods are discussed in another paper given at this conference entitled "Automated Pictorial Pattern Recognition - Data Acquisition" by R. A. Young, D. W. Lywood and J. V. Milligan.

The digital form of the picture when it is ready for processing by the 360/50 is a 32 x 32 matrix containing light intensity values of up to 64 levels. Before any significant pattern analysis can be done, pre-processing procedures must be performed on the data.

A primary goal of pre-processing is the reduction of noise. Certain potential sources of noise seem to be at a minimum in our system; the spectral characteristics of the Vidicon receiver are uniform across its surface, and the optics of the system are quite good. However, uneven illumination across the tube must be corrected, and the picture must be sharpened to bring out contour edges; the smoothing of ragged edges is also desirable. Finally, thresholding must be done to produce a binary matrix in which the contours are clearly defined.

Uniform grey scales are used for illumination correction; it was found that for our system the 90% reflectance card (KODAK) is the best. The grey scale intensity matrix values are used to correct the data matrices. Each value in the data matrix is divided by the corresponding intensity value in the correction matrix. These corrected matrices, after normalization, are further processed.

Smoothing, or "blurring", is accomplished by averaging individual elements with their neighbors after appropriate weighting. With our system, however, this procedure degraded the image and we found sharpening procedures to be more useful.

We have incorporated three sharpening procedures in our program. Initially, a double differentiation is performed over the entire matrix, using a digital version of the "Laplacian" where any element $a_{i,j}$ is replaced by the expression:

$$4a_{ij} - (a_{i-1,j} + a_{i+1,j} + a_{i,j-1} + a_{i,j+1})$$

The result of this operation is a matrix containing a very wide range of values, including negative numbers; this is then added to the first matrix (the matrix to which the differentiation was applied) to normalize the values. Fig. 2 shows a histogram of the distribution of intensity values after illumination correction and Fig. 3 shows the increased range after initial sharpening.

The second sharpening procedure consists of thresholding the matrix which was produced by the previous step. Since the maximum dynamic range of the Vidicon system is 16 intensity levels, the intensity values of the matrix could be divided into 16 groups, each of which contains an equal number of values. This method proved to be unsatisfactory and we developed another using the histograms. The existence of fairly well-defined maxima and minima in the histogram led us to adopt the following method for thresholding: The main peaks are located and the valleys between them are chosen as the cut-off points for the thresholds. In the cases we have studied we have found from 1 to 7 peaks, depending upon the complexity of the picture.

Figure 4 is a five-level printout of the original picture computed automatically from the histogram in Fig. 2. Figure 5 is a binary matrix using intensity level "1" as a cut-off. The increased definition of contours in Fig. 6 will allow the next step in pattern recognition, the definition of closed loops.

ACKNOWLEDGEMENTS

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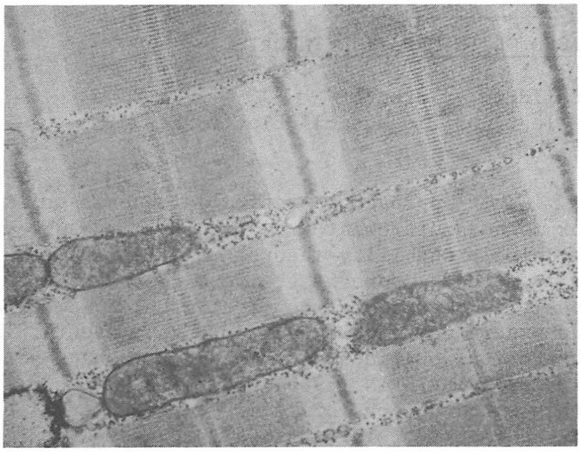

FIGURE 1

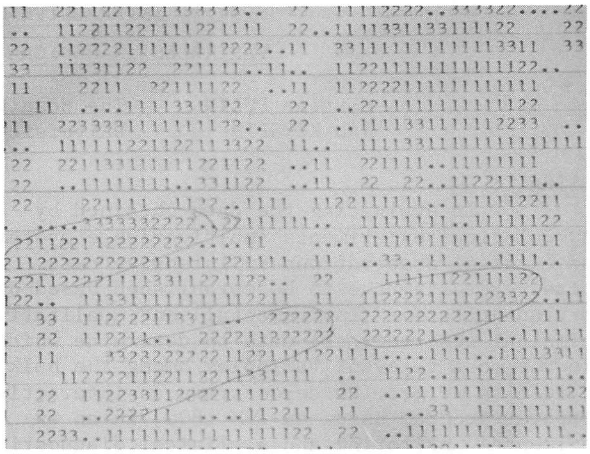

FIGURE 4

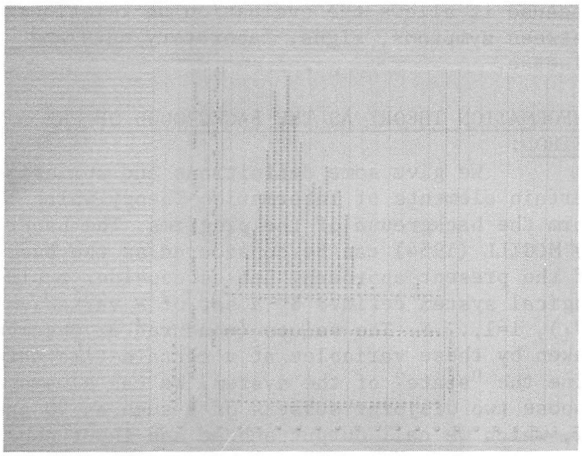

FIGURE 2

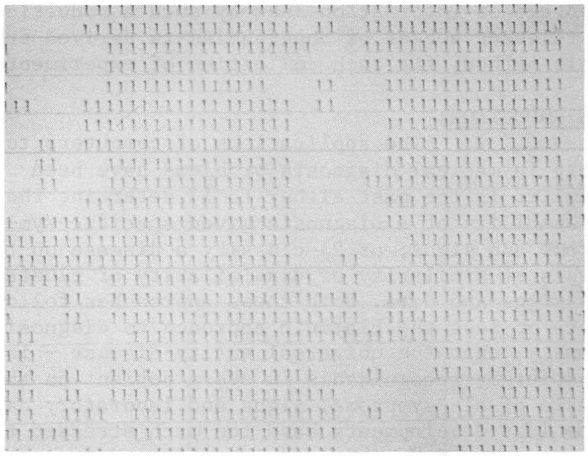

FIGURE 5

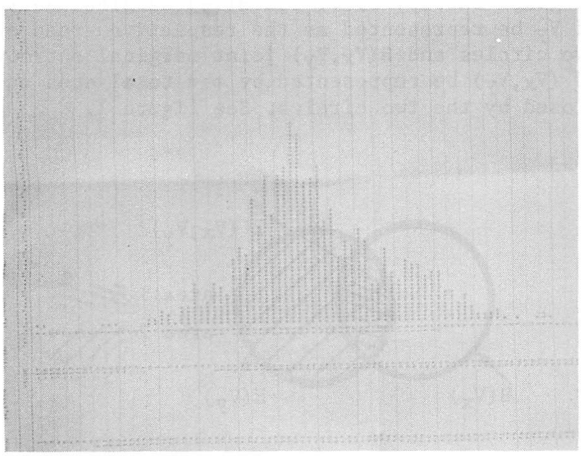

FIGURE 3

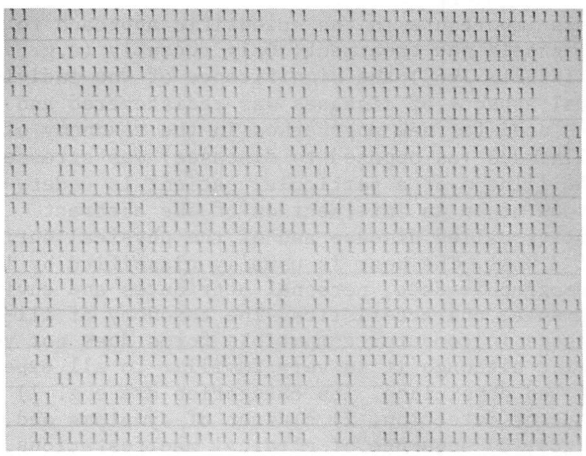

FIGURE 6