It should be noted that for the left- to right-scanning algorithm an adder and registers of double precision are required.

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# The Automatic Counting of Asbestos Fibers in Air Samples

T. PAVLIDIS AND K. STEIGLITZ

***Abstract*—A method is described for automating the counting of asbestos fibers in air samples by computer processing of digitized pictures. Preliminary results show the method is feasible.**

***Index Terms*—Asbestos, asbestos fibers, counting, fibers, image encoding, image processing.**

## I. Introduction

Presently, the levels of hazardous asbestos fibers in certain industrial environments are monitored by human counting from magnified air samples. In this paper we propose a system for accomplishing the same end automatically, by digitizing the microscope image and using a computer program to count the fibers. The results of some preliminary runs are presented to show the ultimate feasibility of such a scheme.

The advantages of automating a monitoring function such as that discussed here are obvious: first, there is the consistency and reliability inherent in an automatic process; second, the speed; third, the ultimate decrease in cost.

The practical implementation of an automatic fiber counting system can be accomplished by either local or remote computing. If local computing is done, there is no communication problem, but the capital cost of a dedicated minicomputer must be considered. If remote computing is done, a large time-shared system can be used, but the communication costs must be considered. The choice between these approaches will be governed mostly by economic considerations. In either case the microscope picture can be digitized by one of the many available techniques. In the present work we digitized photographic prints (Fig. 1) using a TV camera, a scan rate converter and an A-D converter into 256 × 256 pixels with 6 bits/pixel.

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## II. Data Structure and Basic Algorithm

Before any further processing each digitized picture is converted into a graph. This offers an immediate data compaction and simplifies the subsequent processing steps [1], [2]. The conversion is done in the following way: Each raster is scanned for dark areas, i.e., where the brightness is less than some predefined threshold $T$. When a "dark" interval is found it is assigned a number and it is considered as a node of the graph. If two "dark" intervals in adjacent lines overlap then the corresponding nodes of the graph are connected by a branch. Overlap of two intervals is defined if they have at least a pair of cells one directly above the other [Fig. 2(a)]. An alternative criterion is to define overlap if they have a pair of cells with a common corner. [Fig. 2(b)]. We used the first method in the present implementation. The graph is directed through the above-below relation of the intervals corresponding to nodes.

Obviously fiber ends will be mapped into nodes of total degree one [Fig. 2(c)]. However, nodes of total degree one can also occur from bent or split fibers as shown in Fig. 3(a). This configuration will yield a connected component of exactly two nodes. However, the arrangement of Fig. 3(b) yields three nodes of degree one as shown in Fig. 3(d). A multiply bent fiber [Fig. 3(c)] will give a graph of the form shown in Fig. 3(e). On the other hand, two crossing fibers will give the configurations of Fig. 3(f) or (g). It can be seen that any node of total degree one from a bent fiber must be the start of a "downward" path to a node of degree (1, 2) (denotes up-degree = 1, down-degree = 2) or an upward path to a node of degree (2,1) or to a node of degree one. On the other hand, crossing fibers can generate only paths from nodes of degree (0,1) to (2,1) and (2,2) or from nodes of degree (1,0) to (1,2) and (2,2). If the graph is searched and all nodes of degree (0,1) or (1,0) connected by a chain of nodes of degree (1,1) to nodes of degree (1,2) (or (2,1) respectively) are marked then the unmarked nodes of total degree 1 will correspond exactly to fiber ends. Therefore, the number of fibers will equal half the number of such nodes.

The arguments above are based on the assumption that the quantization width is small compared with the thickness of the fibers.

The last assumption seems to hold in most practical situations and the actual number of fibers is uncertain enough so that the above algorithm can be considered as a heuristic. In fact, inspection of Fig. 1 shows that the main problem is the breaking of fibers by nonuniform illumination, resulting in small segments comparable in size to the quantization width.

Obviously further work on more sophisticated algorithms will result in more accurate counts, and the present algorithm is primarily aimed at demonstrating the feasibility of the approach.

## III. Implementation

The procedures described in the previous section were implemented in Fortran and tested on a number of pictures digitized by the method described in Section I. Figure 4 is the digitization of that part of Fig. 1 which is within dotted lines. It is seen that the 256 × 256 matrix does not give high enough resolution for all the available detail. However, it was decided to proceed with these data for two reasons. One was economical and the other had to do with the application. Fibers missed by the 256 × 256 quantization will be of diameter less than $0.2\mu$ and this is below the generally accepted limit of those constituting a health hazard [3].

Fig. 5 shows the graph produced by the algorithm. The numbers indicate the correspondence of nodes of degrees (0,1), (1,0), (0,2), (2,0), and (0,0) with Fig. 4. Nodes #82 and #139 are marked. The count produced by the algorithm is then 8 which is close to a human count on the original picture. (Note that it is difficult if not impossible for human observers to agree on how

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Fig. 1.

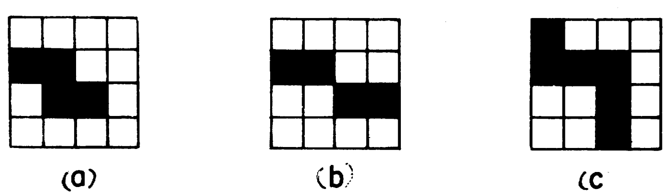


Fig. 2.

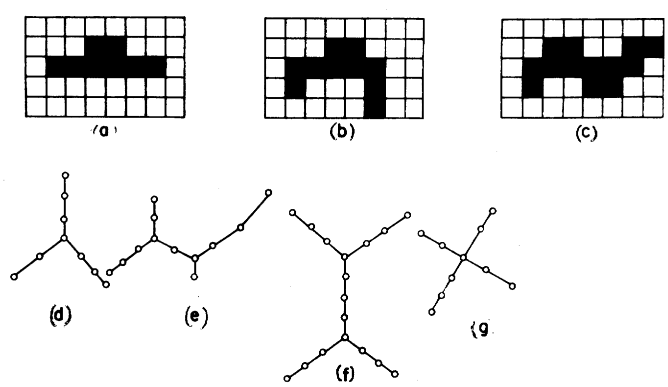


Fig. 3.

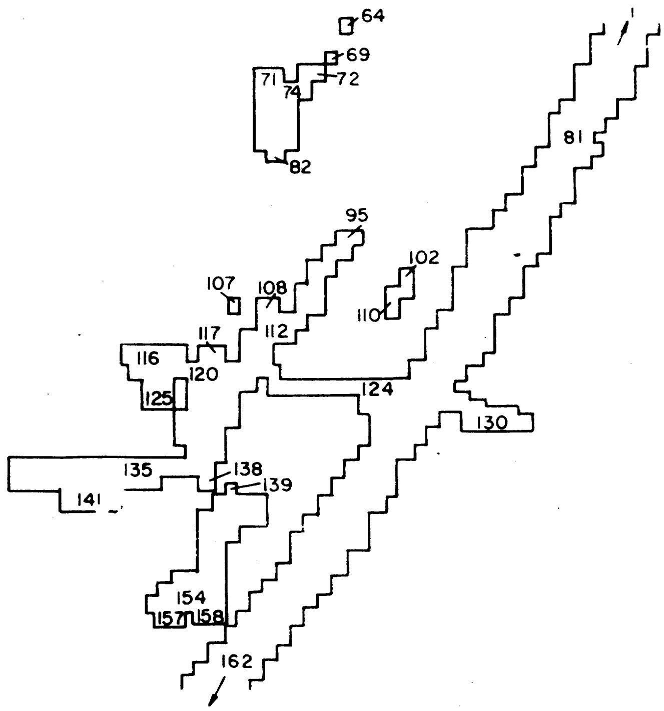

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Fig. 4.

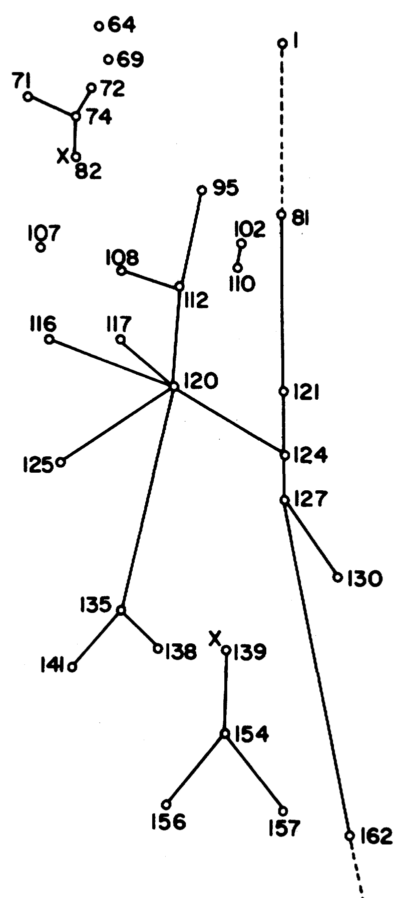

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Fig. 5.

many fibers are in that section.) For the whole picture the total count was 30 fibers.

The algorithm is very fast because after the initial scan (which must be done by any counting method) it deals only with a graph whose number of nodes is a small fraction of the number of pixels.

## IV. Conclusions

We have attempted here to describe the data gathering, reduction, and processing necessary for automating the counting of asbestos fibers; and to demonstrate the feasibility of the proposed scheme with preliminary experiments. Future work along these lines is needed, of course, to develop more refined and efficient data structures, algorithms, and possibly hardware, if the system is to become economically attractive.

## Acknowledgment

We want to thank Bruce Almich formerly of the National Institute of Occupational Safety and Health, Cincinnati, OH for providing us with the sample photographs and suggesting the problem.

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# A Declustering Criterion for Feature Extraction in Pattern Recognition

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***Abstract*—A feature extraction technique based on a new criterion for "*declustering*" is presented. Declustering occurs when sample vectors from one pattern class form a densely packed point constellation, or cluster, in feature space while vectors from another class do not form a cluster but instead array themselves as outliers. Features chosen to optimize the declustering criterion enhance class separation and are robust over a wide range of measurement statistics.**

**The new method is compared to the Fisher linear discriminant function and modified Fukunaga–Koontz transformation using both simulated and actual data taken from a set of breast thermograms.**

***Index Terms*—Clustering, feature extraction, linear transformation, nonparametric classification, pattern recognition, principal component analysis, Rayleigh quotients.**

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## I. Introduction

The goal of a pattern recognition system is to process a set of measurements which are taken from the physical world and decide into which of several prespecified classes the measurements should be assigned. Since the measurement transducers normally are chosen with regard to economic rather than pattern recognition considerations, the measurement set, represented by a vector in a $N$-dimensional space,[1] contains information which may not be required for the pattern classification. The feature extraction (FE) problem is to map the measurement space $X = \{\boldsymbol{x}\}$ into a $K$-dimensional feature space $Y = \{\boldsymbol{\gamma}\}$, where $K$ is much less than $N$, while retaining the class discriminatory information.

Early FE methods represented the measurement signals by a weighted sum of orthogonal functions and used the set of weighting coefficients as the feature set, as in Fourier series analysis [1]. However, FE techniques which are designed to provide a good representation of the measurement set may discard the discriminatory information necessary for satisfactory performance by the pattern classifier. Therefore in this correspondence, attention was focused on ways of extracting those features which emphasize class discrimination.

The FE problem can be formulated as an optimization problem by defining a criterion functional over a class of admissable transformations. The criterion functional is chosen to measure the effectiveness of a feature set in discrimination between pattern classes. One possible functional is a metric on the set of probability density functions (pdf's). Some examples are the Bayes' probability of error and the Bhattacharyya distance [3]. However, in many practical pattern recognition problems the class conditional pdf's are not known and must be estimated from a set of labeled data samples. The resulting storage and computational effort required to optimize the criterion can exceed the capabilities of the available computing hardware, and such criterion functionals have had limited application in practice [4].

Functionals based on the lower order moments of the class conditional pdf's have had a much wider acceptance. Usually these functionals are not monotonic functions of the Bayes' error, but often they perform satisfactory. In addition they are simple to compute and, in many cases, the optimum FE transformation can be found analytically. Examples of such functionals, defined for linear FE transformations, are the Fisher criterion [5] and the Declustering Criterion [6], [7]. Furthermore, although not developed in terms of a criterion functional, we will show, in a later section, that an FE algorithm by Fukunaga and Koontz [8], modified by Sanyal and Foley [9] is the realization of the optimization of an implied criterion functional.

This correspondence presents a new FE technique based on the declustering criterion [6], [7]. Bounds on the performance of this technique, assuming Gaussian pdf's, are derived. Finally a comparison is made of the new technique with existing techniques on both simulated data sets, and actual data taken from breast thermogram scans.

## II. Declustering Criterion

When screening measurement data to produce a binary class assignment, it is not reasonable to expect sample feature vectors from each class to form densely packed clusters. For example, sample vectors from one class may form a cluster while vectors from another class may fall anywhere outside the first cluster. Those vectors which do not cluster are said to *decluster* [6], [7]. An example of declustering in a two-dimensional feature space is illustrated in Fig. 1.

[1] Vectors are boldface italic.

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