Picture Recognition Method Using Line Element Analysis

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Abstract

This paper presents a method to recognize binary pictures by transforming the picture patterns into a line graph and analyzing the line graph topologically.

In order to introduce the method, basic segments composing the line graph, which involves a direction property and connection property, are defined as line elements. Line graph is analyzed by the line elements, so that a method to recognize line graph structure is established.

The usefulness of this method is verified by computer simulation.

1. Introduction

In picture recognition, the edge extraction is one of the most basic and significant process. If a picture pattern can be transformed into a fully thinned line graph image, the information to be recorded is greatly reduced and effective geometrical properties can be preserved. Further, a line graph involves a merit in which its structure analysis is relatively easy.

This paper proposes a method to recognize binary pictures by transforming the picture patterns into line graph images and analyzing the line graphs topologically.

In this paper, basic segments composing the line graph are defined as line elements. The line elements involve a standardized direction and connection property. Geometrical structure in a line graph is analyzed by the line elements, so that features are extracted.

This feature extraction algorithm utilizes a method to describe a picture pattern by polynominal expansion[1)].

Further, the local property of picture computation, based on line element analysis, is evaluated and an efficient picture recognition method is realized.

Finally, in order to verify the usefulness of this approach, computer simulation experiments are performed.

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2. The feature extraction algorithm

Line segments, which are the significant concept of this research, are defined and the feature extraction algorithm is introduced.

2.1 Preparation

As preparation to introduce this algorithm, some notations and definitions are given. Let picture space U, in which a line graph is defined, be 2 - dimensional space. Define the picture space U as M x N array, where each element is given by pixel $X_{i,j}$.

Giving a black pixel and white pixel by symbols, $x_{i,j}$ and $\bar{x}_{i,j}$, respectively, a line graph is defined as follows;

$$L_s^t = \{X_{i,j} | X_{i,j} = x_{i,j}\} \text{ , } s = 1, 2, \dots , \alpha, \; t = 1, 2, \dots , \beta s,$$
$$L_s^t \subset U,$$

Where s represents a line graph category, while t is a line graph number belonging to each category.

Letting P(s) and P(t|s) be defined as the prior probability of a line graph category s and the conditional probability of a line graph L_s^t belonging to a category s, respectively, the following formula is introduced.

$$\sum_{s=1}^{\alpha} P(s) \sum_{t=1}^{\beta s} P(t|s) = 1. \qquad (1)$$

2.2 Definition of line element

A pixel in square mesh space is connected with its neighboring pixels by two modes; point-to-point connection and edge-to-edge connection, as shown in Fig.1.

Based on these connection modes, we can define eight direction properties for neighboring pixels, as shown in Fig.2.

point-to-point connection   edge-to-edge connection

Fig.1 Connection patterns of neighboring pixels

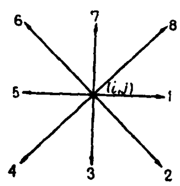

Fig.2 Direction patterns of line graph

Thus, line elements are given as a pixel run involving a connection and direction property as shown in Fig.3.

That is, by letting the direction properties 1 and 3 be positive coordinate representation, we define the line elements as follows, ① line element of direction property 1

$$\bar{x}_{i,j}\ x_{i+1,j}\ \cdots\ x_{i+\nu-1,j}\ \bar{x}_{i+\nu,j}$$

② line element of direction property 2

$$\bar{x}_{i,j}\ x_{i+1,j+1}\ \cdots\ x_{i+\nu-1,j+\nu-1}\ \bar{x}_{i+\nu,j+\nu}$$

③ line element of direction property 3

$$\bar{x}_{i,j}\ x_{i,j+1}\ \cdots\ x_{i,j+\nu-1}\ \bar{x}_{i,j+\nu}$$

④ line element of direction property 4

$$\bar{x}_{i,j}\ x_{i-1,j+1}\ \cdots\ x_{i-\nu+1,j+\nu-1}\ \bar{x}_{i-\nu,j+\nu}$$

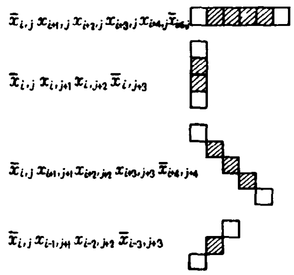

Fig.3 Line element examples

The ends of each line element must be white pixels.

Line elements are generally represented by the following symbol

$$r(\mu,d)$$

where

μ ; run length of line element (number of pixels composing the line element)

$$\mu = \nu + 1 \text{ and } \mu \geqq 3,$$

d ; direction property

$$d = 1,\ 2,\ 3,\ 4.$$

The number n of all sorts of line elements below run length $\mu (\geqq 3)$ is calculated with the following formula.

$$n = (\mu - 2) \times 4 \text{ (direction)} \tag{2}$$

2.3 Geometrical structure analysis and feature extraction

We attempt to analyze line graph structure by line elements and extract features from line graph L_s^t.

Assuming that a fully thinned line graph L_s^t is composed of the line elements, let us represent line graph L_s^t as

$$L_s^t = \{r(\mu,d)\} \tag{3}$$

where $\mu = 3, 4, 5, \ldots$, $d = 1, 2, 3, 4$.

Hereafter, $r(\mu,d)$ is simply given by symbol $r_{\mu d}$.

By regarding the line elements in eq.(3) as feature components of line graph L_s^t, the following linear expansion is obtained

$$L_s^t \underset{\mu n}{\approx} \sum_{\mu} \sum_{d} a_{\mu d}^{st}\, r_{\mu d} \quad , \tag{4}$$

where symbol $\underset{\mu n}{\approx}$ shows that line graph L_s^t can be described by line elements (feature components) having a run length at most μn.

In eq.(4), each $a^{st}_{\mu d}$ corresponds to a feature coefficient (i.e. feature) for a feature component $r_{\mu d}$. Strictly speaking, $a^{st}_{\mu d}$ indicates the number of times that line element $r_{\mu d}$ is contained in Line graph L^t_s.

These features involve various geometrical properties because the line elements have the ability to extract effective information in straight segments, curve segments, crossing points, end points and branching points of the line graph.

The features will be represented by the vector

$$A = (a^{st}_{31}\ ,\ a^{st}_{32}\ \dots\ ,\ a^{st}_{\mu d}\ ,\ \dots\ )^t, \qquad (5)$$

where t denotes the transpose operation.

Performance of feature component $r_{\mu d}$ can be evaluated by eq.(1) as

$$a_{\mu d} = \sum_{s=1}^{\alpha} P(s) \sum_{t=1}^{\beta s} P(t|s)\ a^{st}_{\mu d}\ . \qquad (6)$$

3. The picture recognition system

In order to realize an efficient picture recognition system based on this feature extraction algorithm, we describe an algorithm to search the line element and evaluate the locality of data processing. The line elements are extracted by the searching of the pixel run in four coordinate directions, as shown in Fig.4.

This search algorithm is performed only when the start point $x_{i,j}$ of the pixel run is white and the neighboring pixels of the point $x_{i,j}$ are black.

If the black pixel run is continuous in one direction, the search process is repeated until the white pixel is searched or the frequency of this process reaches the upper limit of run length, previously given.

Because this data processing efficiency is based on run length μ, the smaller the value of μ, the simpler the search process.

However, if the run length μ is set in large value, the number of features will increase, as shown in eq.(2), then picture description becomes more exact. Therefore, an optimum run length is required.

Based on the relationship just described, we define a function to evaluate the optimum run length μ, as follows

$$P = g\{f\ (A),\ \mu\}\quad , \qquad (7)$$

where g is a function to calculate the picture recognition probability p, obtained in picture classification, depending on features extracted by line elements having at most run length μ and a discriminant function f(A).

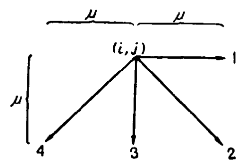

Fig.4 Search direction patterns of line element

By specifying a fixed recognition probability p^*, the most appropriate run length μ^* is calculated as follows

$$\min_{\mu}\{g(f\ (A),\mu)\geq p^*\} = g\ (f\ (A),\ \mu^*)\,. \qquad (8)$$

Accordingly, if an appropriate parameter p^* is given in eq.(8), the optimum value μ^* can be determined, and an efficient picture recognition system will be realized.

4. Computer simulation

In order to verify the effectiveness of this approach, a computer simulation was performed. In this computer simulation, features were extracted from a line graph. The line graphs were classified by the features into two groups. Linear discriminant function was applied to classification.

4.1 Line graph data and line elements

Line graph data, generated from 41 lymphocyte and 35 monocyte images, are given for this computer simulation. Samples of these data are shown in Fig.5.

Thirty two line elements below run length μ = 10 were applied to this computer simulation.

Picture space U was a 72 x 72 pixel array.

4.2 Simulation results and evaluation

4.2.1 Feature extraction

Picture space U, where line graph L_s^t exists, was analyzed by 32 line elements, and a feature set $\{a_{\mu d}^{st}\}$ was extracted from L_s^t . These results are shown in Table 1.

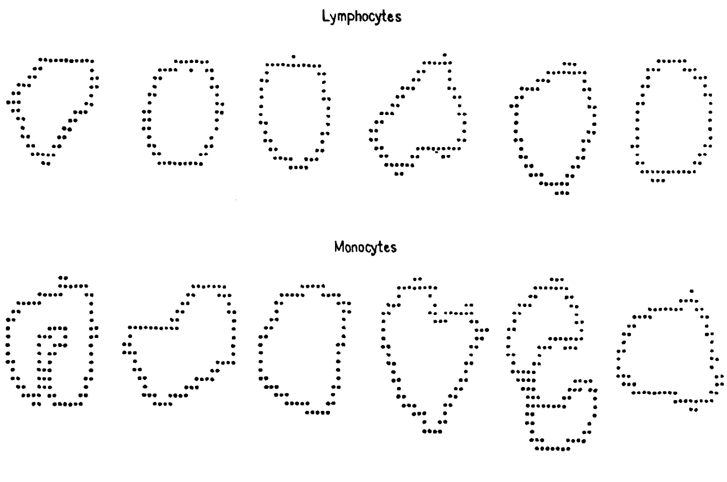

Fig.5 Line graph samples for white cell nuclear picture

In Table 1, parameters $a^{(1)}_{\mu d}$ and $a^{(2)}_{\mu d}$ are averages of the feature set $\{a^{st}_{\mu d}\}$ of 41 lymphocytes and 35 monocytes. $S^{(1)}_{\mu d}$ and $S^{(2)}_{\mu d}$ indicate these standard deviations.

Effectiveness gives a statistical performance of features. It is calculated on the basis of parameters $a^{(1)}_{\mu d}$, $a^{(2)}_{\mu d}$, $S^{(1)}_{\mu d}$, $S^{(2)}_{\mu d}$ 2).

As shown in Table 1, this computer simulation proved the fact that the effectiveness degrees relatively decrease, as run length μ becomes larger.

The above tendency is particularly conspicuous for μ beyond 6.

Therefore, we can set up a relatively small value of μ, so that it is very favorable to realize an efficient picture recognition system based on local picture processing.

4.2.2 Picture classification

Figure 6 shows results which 41 lymphocytes and 35 monocytes were classified by a feature set $\{a^{st}_{\mu d}\}$ and a liner discriminant function model f(A).

Recognition probabilities, corresponding to the number n of features, were obtained. Recognition probability of $\mu = 5$ was over 90%.

However, if number n of the features is beyond 16 ($\mu = 5$), the rate of rise of the recognition probability tends to diminish. That is, the following relation is satisfied by giving 0.9 (90%) in eq.(8).

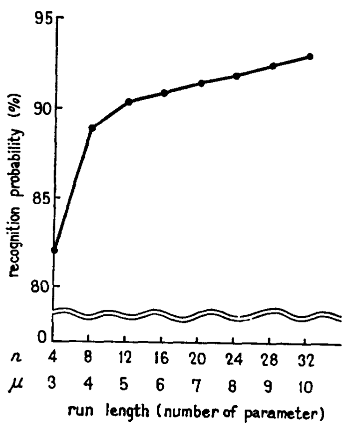

Fig.6 Relationship between recognition probability and run length μ

Table 1 Average and standard deviation for parameter $a^{st}_{\mu d}$ of limphocytes and monocytes

Line Element μ	Line Element d	Lymphocyte Average $a^{(1)}_{\mu d}$	Monocyte Average $a^{(2)}_{\mu d}$	Lymphocyte Deviation $S^{(1)}_{\mu d}$	Monocyte Deviation $S^{(2)}_{\mu d}$	Feature Effectiveness
3	1	10.52	13.03	3.49	4.72	31
	2	29.33	39.71	7.23	8.12	68
	3	10.10	14.61	3.23	5.35	53
	4	26.31	33.84	5.79	6.17	63
4	1	10.69	14.06	2.58	3.32	57
	2	4.71	8.35	2.02	3.53	66
	3	10.60	14.61	2.65	3.80	62
	4	5.00	8.97	2.84	3.67	61
5	1	2.29	4.00	1.52	2.22	46
	2	1.55	2.52	1.13	1.26	40
	3	2.86	3.87	1.28	2.39	28
	4	1.55	2.32	1.17	1.74	27
6	1	0.93	1.52	1.13	1.09	26
	2	1.17	1.35	1.01	0.98	9
	3	0.76	1.06	0.91	0.96	16
	4	1.10	1.61	0.76	1.33	25
7	1	0.48	1.00	0.71	1.00	31
	2	0.74	0.90	0.66	0.83	11
	3	0.52	0.71	0.71	0.94	11
	4	0.64	0.52	0.76	0.68	9
8	1	0.50	0.55	0.59	0.62	4
	2	0.26	0.32	0.45	0.54	6
	3	0.69	0.58	0.75	0.76	7
	4	0.17	0.58	0.38	0.72	38
9	1	0.36	0.32	0.58	0.65	3
	2	0.05	0.13	0.22	0.34	15
	3	0.17	0.42	0.38	0.56	27
	4	0.14	0.23	0.42	0.50	9
10	1	0.43	0.81	0.59	0.83	27
	2	0.07	0.06	0.26	0.36	1
	3	0.38	0.81	0.54	0.87	30
	4	0.10	0.16	0.30	0.45	9

$$\min_{\mu} \{g(f(A), \mu) \geq 0.9\} = g(f(A), 5).$$

In view of these results, we have introduced the conclusion that the effectiveness of the features and the recognition probability reached the limit level at run length $\mu = 5$.

Thus, though we chose lymphocytes and monocytes, as shown in Fig.5, whose classification seems to be quite difficult, relatively high recognition probability was acquired by 12 local line elements at most $\mu = 5$.

This computer simulation was performed by using the large-scale computer TOSBAC-5600 system. The computer simulation process time was about 30 seconds.

5. Conclusion

This paper has described an algorithm which can recognize effective geometrical properties by analyzing the line graph structure.

It is believed that this algorithm can be applied for various kinds of pattern recognition problems, e.g. shape recognition of binary picture, picture structure analysis, handwritten character recognition, etc.

References

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