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Inductive Learning of Primitive Shape Features of Closed Contours

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Abstract

A method for inductive learning of primitive features is proposed. Primitive features are well investigated and they are extracted in bottom-up manner from training set of patterns by a segmentation method based on genetic algorithm. Merging is applied to selected primitive candidates to filter out their redundancy as similarity and inclusion. Experimental results with map figures are shown.

1 Introduction

Researches of inductive or bottom-up learning of primitive shapes or features have been one of the major fields in pattern recognition and understanding. They are called feature definition and feature selection [1]. In many methods for visual pattern recognition, no matching procedure can be effective without well organized primitive features defined for an expected set of object patterns. Otherwise, many heuristics introduced into programs for pattern recognition and image processing, such as threshold parameters and regions of interest, are very difficult to determine reasonably because that the primitives are given in a top-down manner and no formalized knowledge effective for evaluation can be utilized in real situation. In application fields of image pattern recognition, algorithms for automatic definition of primitive features are desired to handle many new products. But there are few systematic ways for deriving primitive features in bottom-up manner from given samples of object shapes.

We have proposed an inductive learning method based on genetic algorithm for automatic extraction of primitive shapes of closed contour, such as alphabetic characters and symbols [7]. In this paper, we presents some modifications of the method and experimental results with real objects.

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2 Primitive shapes

We have the following assumptions on fundamental characteristics of primitive features:

(1) Primitive features should be defined by similarity of shapes.
(2) They should be defined by frequency. If we can find even very small features in not so few objects, they can not be omitted from fundamental primitive features.
(3) They may be defined by some difference. For discrimination of disjoint classes, different features can be utilized effectively.
(4) They should have as large bodies as possible. We expect a level of data compression with well-defined primitive features.
(5) They should be independent from each other. It is preferred for any primitive features to have low redundancy.
(6) They should have capability of describing object shapes in a reasonable description length.

It has been popular to call a particular set including a small number of simple shapes "the primitive set". In this paper, however, we use the word "primitive features" to represent more primal shapes in the hierarchy of human perception[3]. In this study, the characteristics (3) is out of the scope because it seems sufficient for many problems to adopt only similarity measure for class discrimination.

3 General scheme

There are some possible way to define primitive features. For example, for a given object shape one may be possible to imagine a rectangle fitting to the shape as a whole. Another may break the shape into some pieces and then reconstruct local pieces to the whole one. These local features can be recognized as alphabet symbols in the formal language theory[4]. In this study, we adopt the latter way of defining primitive features as local parts of object shapes.

Clustering is one of the methods for unsupervised learning based on similarity measure and the least square fitting is a typical algorithm of data compression for data sets with uniform components [1]. It is, however, rather dangerous to apply the same approaches to extract primitive features from non-uniform training data. If a line is fitted to a set of non-uniform components with high dispersion, the results may be meaningless because of some outliers. The similar situation will occur when one wants to extract primitive features inductively. To keep robustness against non-uniform data, global or local mode selection techniques have been proposed for bottom-up geometrical parameter estimation [8]. We apply this kind of principle to design our method.

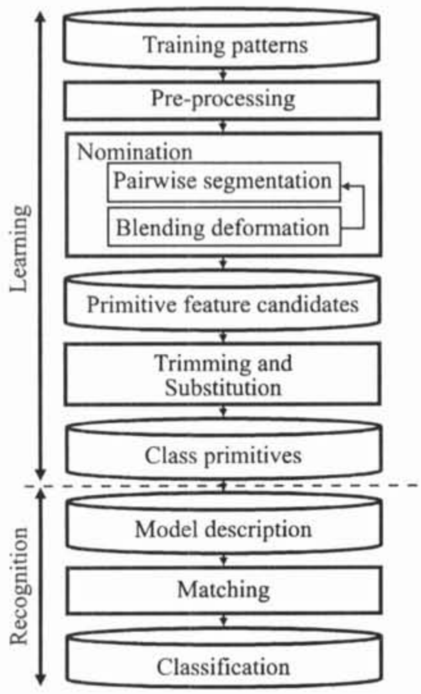


Fig. 1 General scheme.

Fig. 1 shows a general scheme of our method. After pre-processing, nomination of primitive candidates as parts to describe training patterns is carried out and then primitive feature candidates are output to the file. At the last step of learning, trimming and substitution are performed for selecting and merging similar features and omitting redundant ones. Using class primitives, we can describe models in classes and classify an object into a reasonable class in recognition.

4 Nomination of primitives

A segmentation method consists of iterative application of the following two phases: pairwise segmentation and blending deformation.

4.1 Pairwise segmentation

The assumption (1) described above is a key condition to design segmentation algorithm. Prominency of feature have been proposed based on information theoretical analysis which apply a entropy measure to the given feature set[6]. The prominency of any feature must be relative and dependent on "circumstance" which consists of the other features: the same feature can have different prominency depending on neighbor features.

In order to give such a context dependent attribute to each primitive feature, any pair of objects of the same class have to be considered in segmentation. Each pair consists of a shape called "segmentee" which is segmented into parts, while a counterpart called "make" which is a standard sample and supposed to be a bank of parts. Segment boundaries are optimized by a genetic algorithm where a gene or an individual represents a combination of boundaries defined on the contour of a segmentee as shown in Fig. 2.

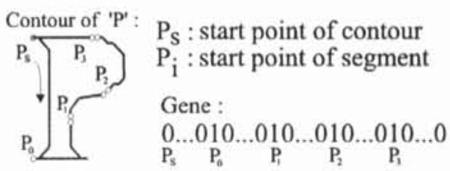


Fig. 2 Representation of gene.

Crossover operation is performed at two positions on a gene and mutation is performed by exchange between "1" and "0". In the algorithm, the parameters are defined as follows: P: population size, G: generation number, S: initial segment number, M: mutation probability, C: crossover probability and B: blending number. The fitness criteria are defined as follows:

$$F = \frac{1}{n+N}\sum_{i=1}^{n}(L_i - \delta \cdot d_i)$$

where n is the total number of segments, d_i the difference with respect to the i-th segment. For any pair, each segment of a segmentee is selected and scanned along the contour of a make in order to evaluate how good the segment is. According to this fitness definition, the segmentation with fewer segments of sufficient matching is more preferred and can survive in dynamic generation change [7].

4.2 Blending deformation

In blending deformation, segments with poor matching, such as small noises, are deformed and cleaned away by a simple algorithm based on interpolation as shown in Fig. 3. For any pair, all the segments of a segmentee are sorted in the order of the fitness value. Segments with high fitness can be useful to assert local similarity of the two constituents. On the other hand, segments with low fitness have to be deformed to search more primitives. A segment with low fitness value is blended with the most fitted part of the make. This approach can be regarded as "mini-max approach" which evaluates a criterion to maximize the near minimal values. By this deformation, the two contours can be blended without loss of resolution such as scale space filtering where a uniform degradation procedure is executed on the whole contour.

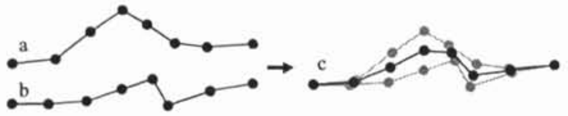


Fig. 3 Deformation.

By this procedure, furthermore, even small and strange features can be enhanced when the both shapes have them as common parts as shown in Fig. 4, where the two small horns of the shape "I" can survive as a primitive feature in the pair 1, otherwise, they are cleaned away in the pair 3.

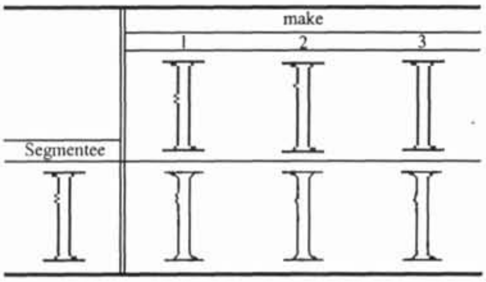


Fig. 4 Effects of blending deformation.

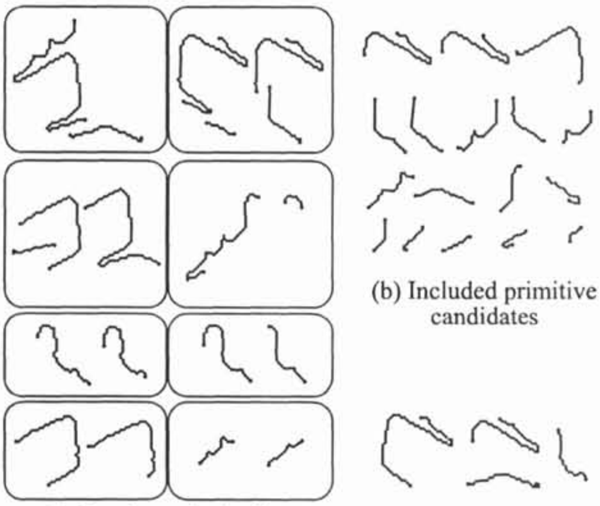
After the iterative applications of the above two procedures to all the pairs from the training set, we can get primitive features for describing and discriminating original shapes with a certain redundancy. We will need some more additional procedures, for example, to find and omit the same or similar primitives from the primitive candidates.

Fig. 5 shows examples of training patterns of "air port" and "public house" from legends in a Japanese domestic map which is magnified by 5.6 times. Fig. 6 is closed contours of their input pictures scanned by 120 dpi. Fig. 7 shows extracted primitive candidates for the air port. We have 40 candidates for the air port and 25 for the public house. The specifications of the experiments are as follows: P=51, G=200, S=0.5 × (peripheral length), M=0.01, C=0.6, B=3, N=15 and δ =0.6. Three kinds of primitive candidates can be considered as shown in the figure. The candidates in (a) include others to some extent so they might be reorganized into smaller ones shown in (b), which are completely included by the ones in (a). The candidates in (c) might be independent of others because they are remained ones except those in (a) and (b).

(a) Air port (b) Public house

Fig. 5 Original pictures.

Fig. 6 Closed contours.



(b) Included primitive candidates

(a) Overlapped primitive candidates

(c)others

Fig. 7 Primitive candidates for air port.

5 Trimming and substitution

Fig. 8 is a schematic illustration of trimming and substitution. Using the matching procedure in the segmentation algorithm, some primitive candidates are overlapped according to some criteria for combinatorial optimization of candidates. They can be divided into some pieces at end points of each primitive. They are substituted by common shapes which are defined as new primitives and then redundancy may decrease while independency may increase. Fig. 9 shows an example of inclusion detected in a primitive candidate for the air port.

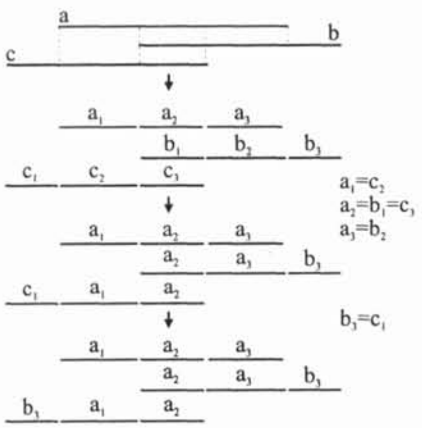


Fig. 8 Trimming and substitution.

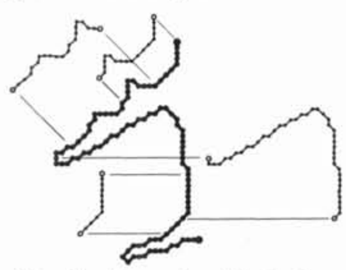


Fig. 9 Example of inclusion.

6 Conclusions

The new inductive learning method of primitive features has been proposed with the verification by the experimental results. The method is efficient to extract primitive features from a given sample set of connected closed contour shapes. The extracted primitive features have rich information on the object shapes and great potential to be utilized for automatic generation of a pattern recognizer.

We are designing the algorithm for trimming and substitution. It is necessary to implement the algorithm and to evaluate its effectiveness for real example.

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