Number Recognition Using Inductive Learning on Spiral Architecture

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Abstract

In this paper, a number recognition algorithm on Spiral Architecture is proposed. This algorithm employs RULES-3 inductive learning method and template matching technique. The algorithm starts from a collection of samples of numbers or letters used in number plates. Edge maps of the samples are then detected based on Spiral Architecture. A set of rules are extracted using these samples by RULES-3. The rules describe the frequencies of 9 different edge masks appearing in the samples. Each mask is a cluster of 7 hexagonal pixels. In order to recognize a number plate, all characters (digits or letters) are tested one by one using the extracted rules. The number recognition is achieved by the frequencies of the 9 masks.

Keywords: Spiral Architecture, hexagonal structure, number recognition, inductive learning, template matching

1 Introduction

Number recognition is playing an important role in image processing field. In the international trade, as a result of the accelerated development of global industries, thousands of containers and trucks need to be registered every day at container terminals and depots. Normally, this registration will be done manually. However, this is not only prone to error but also slow to meet the increasing volume of containers and trucks. Hence, an automatic, fast and exact number recognition process is required.

The fundamental issue in number recognition is shape analysis. Many methods on shape analysis have been seen in the past ten years such as methods using Morphological Functions [1], methods based on gradient propagation [2] and methods by comparing weighted shape graphs [3]. Many other techniques such as Fourier description, template matching [4], invariant moments or neural network [5] are also used for shape analysis.

In order to improve the performance of recognition and to speed up processing, an algorithm on number recognition was achieved in [6] based on Spiral Architecture (SA). The method in [6] obtains a feature vector based on extracted contours of characters that is invariant to affine transformations. One advantage of using this method is that the detection results are robust to image rotation, translation and scaling. However, it cannot distinguish digits 6 and 9 without additional observation and the cost for computing the invariant vector is high for each digit.

In this paper, we propose another algorithm for number recognition. This technique uses RULES-3 [4] induction algorithm to train character samples and obtain the rules that are used to recognize the digits and letters on number plates. The proposed algorithm is based on the edge masks defined on SA.

The organization of this paper is as follows. In Section 2, Spiral Architecture is reviewed and edge masks on SA are defined. In Section 3, RULES-3 is briefly introduced and an inductive learning operation based on the edge masks is demonstrated. Contour extraction (and edge detection on SA) is shown in Section 4. The algorithm for number recognition is proposed in Section 5. We conclude in Section 6.

2 Edges on Spiral Architecture

Spiral Architecture [7] is inspired from anatomical considerations of the primate's vision. From the research about the geometry of the cones on the primate's retina, we can conclude that the cones' distribution has inherent organization and is featured by its potential powerful computation abilities. On SA, an image is represented as a collection of hexagonal pixels [8]. Each pixel is assigned an integer of base 7 starting from 0 (see Figure 1). The assigned integers are called *Spiral Addresses* of pixels. On Spiral Architecture, two algebraic operations have been defined, which are Spiral Addition and Spiral Multiplication [7]. These two operations can be used to define two transformations on SA respectively, which are translation of image and image rotation with scaling. Under a Spiral Multiplication, the original image is segmented into several parts. Each part is a similar copy of the original image rotating in some degree. In this paper, Spiral Multiplication will be used to make seven similar copies of the original image so that the characters in these image copies (or parts) can be processed in parallel. The results from these parts will be summed up. In this way, the correctness of the final result is improved and the algorithm is more robust to noise. Moreover, these seven copies can be distributed to seven machines to be processed independently, so the processing time is greatly reduced.

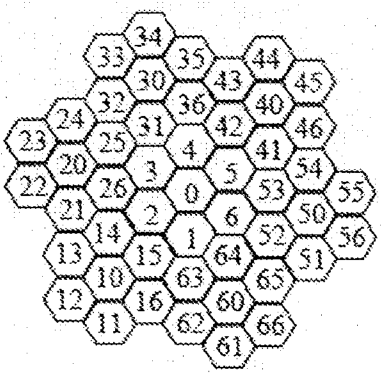


Figure 1. 49 hexagonal pixels labeled by spiral addresses

In [4], twenty 3×3 edge masks on traditional image (square) structure were defined. In Figure 2, we define nine edge masks that cover all possible cased because of the special image structure on SA. Each mask is a cluster of seven hexagonal pixels. These masks will be used for inductively learning the rules in the next section and for number recognition algorithm in Section 4.

3 Inductively Learning Rules

Inductive learning is *a method of moving from the particular to the general – from specific to samples to general rules* [4]. Induction is a process of generalizing a procedural description from presented or observed samples. These samples can be a good tutorial set specified by an expert. An induction process is to find a function of attributes from samples to classify objects, for example, digits and letters. RULES-3 [4] is a simple algorithm for extracting a set of classification rules from a collection of samples for objects belongs to one a number of known classes. An object must be described in terms of a fixed set of attributes, each with its own range of possible values. In this paper, we use the 9 masks defined in Figure 2 as attributes and the frequencies of the masks appeared at the edge maps containing a number (a digit or a letter) each as their corresponding values.

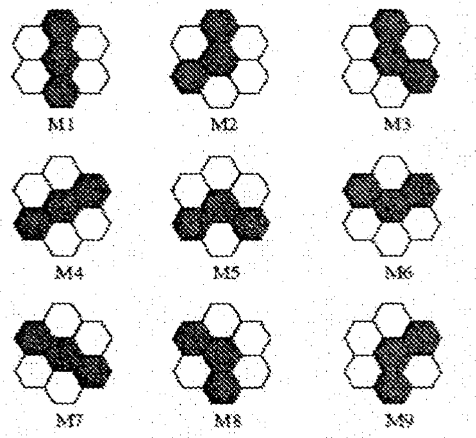


Figure 2. Edge masks on SA

RULES-3 extracts rules by considering one sample at a time. It forms an array consisting of all attribute-value pairs associated with the object in that sample. The total number of elements in the array is equal to the number of attributes used. In our case for number recognition on SA using the 9 edge masks defined, there are 9 elements in the array. In this paper, the rule forming procedure requires 9 iterations per sample. In the first iteration, rules (conditions) will be produced for the first element of the array. After that, the rules for the remaining elements will be examined in turn as in the 1st iteration. After all 9 iterations, the frequency ranges of all characters (digits or letters) for all 9 masks are determined. These determined ranges are then used to classify the characters on number plates. The algorithm for extracting rules is summarized as follows.

Step 1. Take the edge map of a sample character.

Step 2. Set iteration count N_c to 0.

Step 3. If $N_c < 9$, then $N_c = N_c + 1$; ELSE go to Step 5.

Step 4. Find the appearance frequency of N_c-th edge mask (see Figure 2) in the sample. Go to Step 3.

Step 5. Form the rules (the frequency ranges of edge masks) for this sample character. If there are no more unclassified samples, then STOP; ELSE go to Step 1.

4 Edge Detection on SA

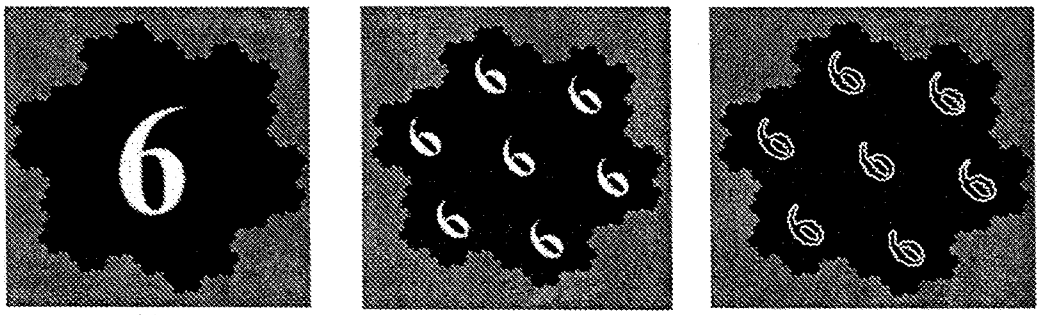
Spiral Architecture is a relatively new and powerful approach to general purpose machine vision system. It contains very useful geometric and algebraic properties. In this paper, we use it to separate the original image into seven near copies. After that, every copy will be processed independently to extract the contours of characters for number recognition. By doing this, we not only shorten the processing time via distributed processing but also create the multiple sets of rules to improve the recognition accuracy.

Spiral Multiplication can achieve uniform image segmentation. Each smaller part after separation is a near copy of the original image. That means each copy results in a unique sampling of the input image. Each sample is mutually exclusive and the collection of all such samples represents a partitioning of the input image. As each smaller part is the scaling down copy of the original image, each copy has less information. However, as none of the individual light intensities have been altered in any way, the scaled images in all still hold all of the information contained in the original. The whole process consists of process down on individual near copies. But the processing time is greatly decreased if we put such processing into a distributed cluster system.

Gaussian Multi-Scale theory introduced by Linderberg [9] is applied here for edge-detection. According to this theory, image brightness function is parameterized. Image is blurred and the noise is removed when the parameter is positive. We can use this theory for edge detection to remove or suppress image noise, and then to simplify the processing tasks. In general, global Gaussian processing provides us the high precision but with the huge computation. On the other hand, local Gaussian processing certainly decreases computation with the comparatively low precision. So it is required to balance the computation and the precision when processing. Fortunately, because the original image has been separated into seven smaller parts before the Gaussian processing and each part is a near copy of the original one as mentioned above, we can still achieve global processing but with shorter time.

Whether the extracted rules can successfully represent the object depends on the quality of image edge. But naturally, the edge map after Gaussian Edge-detection seldom forms a high quality image edge that is required for the object feature measurement due to the gaps left by noise and shading effects, so an edge-point-linking procedure is necessary. In our work, we use a three-step approach of edge-thinning, edge-point-linking and region mergence to improve the edge map quality. After this pre-processing, we can get perfect single-pixel-wide connected boundaries. Figure 3(c) [6] shows an after pre-processing edge map.

As an illustration, the contours of ten standard Arabic numerals as seen in Figure 4 are displayed in Figure 5 [6].



(a) (b) (c)

Figure 3. Image Pre-processing;
a) Original Image; b) Uniform Image Segmentation; c) Edge Map

5 Number Recognition

In this section, we propose a new algorithm for number recognition on SA. In order to recognize a number plate, the following steps are required.

Step 1. Finds edges (contours) of each letter or digit on a number plate.

Step 2. Recognize the letter or digit using the extracted set of rules as described in Section 3.

Step 3. Recognize number plate by bringing all characters used together.

The detailed procedure for number recognition is demonstrated as follows.

When a number plate region is extracted, it is segmented and the images containing individual characters (digits and letters) forming the number

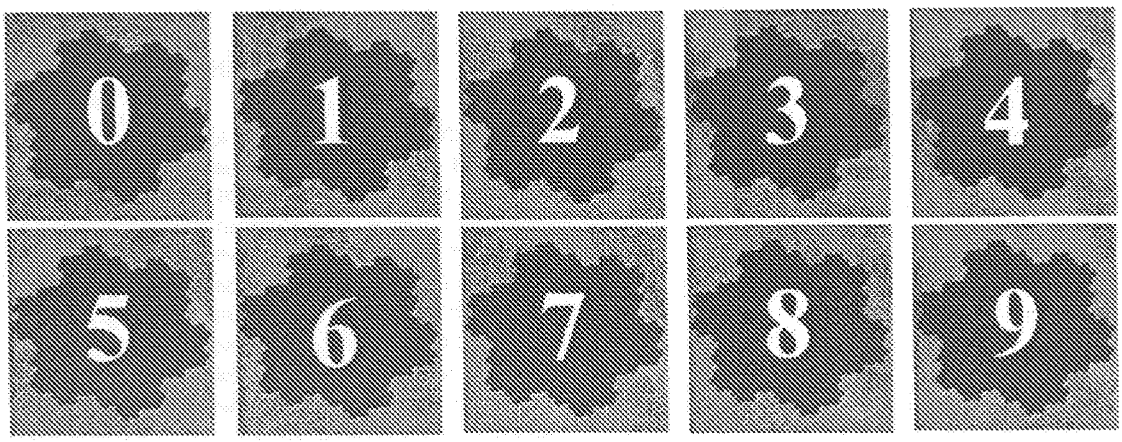


Figure 4. Ten Standard Arabic Numerals on Spiral Architecture

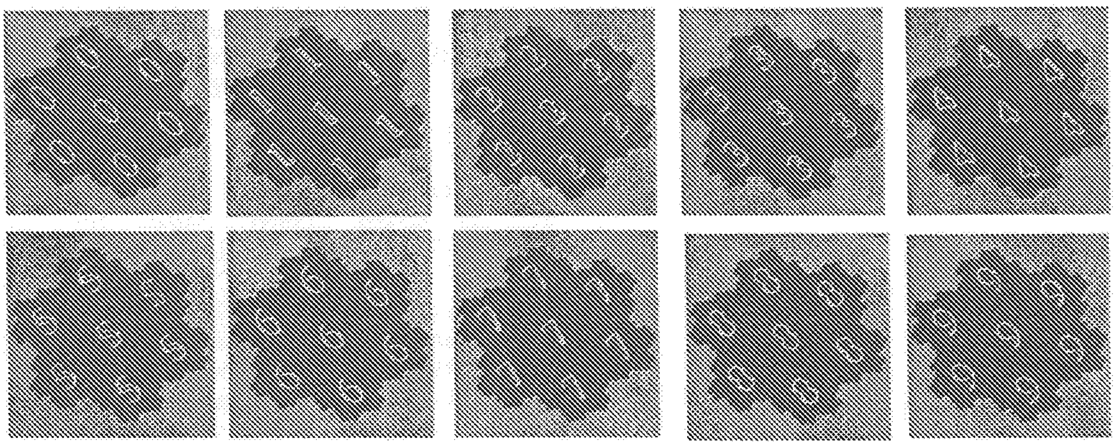


Figure 5. Outmost Boundaries with Different Sections Including the Centre Point of Each Section

plate are obtained. Each image of a character is represented on the Spiral Architecture as shown in Figure 3 (a) and Figure 4. Then a Spiral Multiplication operation is applied to the character to separate the image into 7 sub-images as shown in Figure 3 (b). Edge detection as described in Section 4 is then processed for the sub-images. This is done in parallel. The edge (contour) maps of the character are obtained as shown in Figure 3 (c) and Figure 5.

By applying the edge masks defined in Section 3, the frequencies of the masks for seven sub-images are computed in parallel. By adding the seven frequencies of each mask on the seven sub-images, a summed frequency of the mask is obtained for the character. In the same way, the summed frequencies of all masks of the character are computed. Applying the rules extracted in Section 3, the distance between the sample characters and the tested (candidate) character is computed. This distance is defined in the following:

For each mask M_i ($i=1, 2, ..., 7$) (see Figure 2), let us denote the summed frequency of M_i appeared in the candidate character by C_i and the frequency range of M_i for k-th sample character by $[L_{ik}, H_{ik}]$, where L_{ik} and H_{ik} are two non-negative integers such that $L_{ik} \le H_{ik}$. Note that we need only 36 samples of which 26 are for letters and 10 for digits, so the range of k is from 0 to 25. Let d_{ik} be the distance between C_i and $[L_{ik}, H_{ik}]$ such that

- if $C_i < L_{ik}$, then $d_{ik} = L_{ik} - C_i$,
- if $C_i > H_{ik}$, then $d_{ik} = C_i - H_{ik}$, and
- if $L_{ik} \le C_i \le H_{ik}$, then $d_{ik} = 0$.

Let $d_k = \mathrm{sum}\{d_{ik} \mid i=1, 2, ..., 9\}$ for $k = 0, 1, ..., 35$. We call d_k the distance between the candidate character and the k-th character sample.

The candidate character is deemed matching the K-th sample character if $d_K = \min\{ d_k \mid k=0, 1, ..., 35\}$.

When all character on a number plate are recognized (or classified), the recognition of the number plate is complete.

6 Conclusion

This paper presents the number recognition using edge masks and an inductive learning algorithm on Spiral Architecture. Compared to the RULES-3 based algorithm on traditional rectangular image structure, the number of masks used in this paper has been greatly reduced from 20 to 9 because of the special structure of Spiral Architecture (SA). This not only increases the computation speed but also improves the accuracy of the number recognition because of the symmetric feature of SA. The accuracy and the computation speed are further improved by the uniform separation of input image and parallel processing.

The work in the paper also overcomes the problems of previous work on number recognition on SA such as that there is a difficulty to distinguish digit 6 from 9.

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