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A Bayesian Network Approach for On-line Handwriting Recognition

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6.1 Introduction

On-line handwriting recognition is used to automatically transcribe characters handwritten with electronic devices like tablets and pens. Compared to off-line handwriting recognition, it has the advantage of utilizing time series information of hand movements captured by the electronic devices. Given the widespread use of mobile devices such as cell phones, PDAs and pen computers these days, on-line handwriting recognition has gained large attention again as a convenient and portable input method. Also, its application area has further extended to 3D writing space where a user can draw gestures and characters with inertial sensor-embedded input devices [1].

For highly accurate character recognition, it is necessary to model the structure of characters as realistically as possible. In this Chapter, a character is regarded to have points and basic strokes as its composition structure. The basic strokes are defined as straight or nearly straight traces that have distinct directions from connected traces in writing order. Figure 6.1(a) and (b) shows such examples in numerical and Chinese characters. They are apparently identifiable in the characters with only straight lines like 1, 4 and the Chinese ones. The curvilinear trace, like the lower part of the character 5, can be approximated with several ones.

To describe and identify characters, strokes and their relationships are important (for simplicity, a *stroke* will be used as a shorthand notation of a *basic stroke* in this chapter even though it usually refers to a set of consecutive points from pen-down to pen-up movement). Figure 6.1(b) shows one example. The two Chinese characters have same number and kinds of strokes. However, they belong to different character classes because of difference in stroke relationships; the vertical stroke of the left character is located below the top horizontal stroke. However, that in the right character is located across the top horizontal stroke.

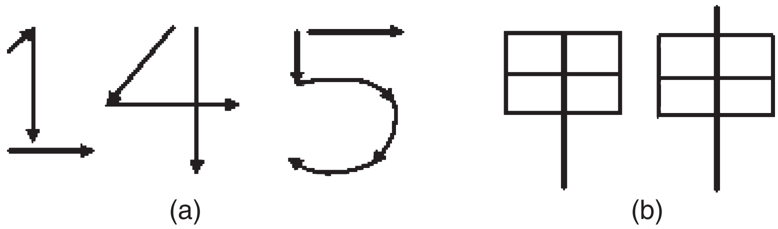

Fig. 6.1. Basic strokes of numerical and Chinese characters. The two Chinese characters belong to different classes because of difference in stroke relationships.

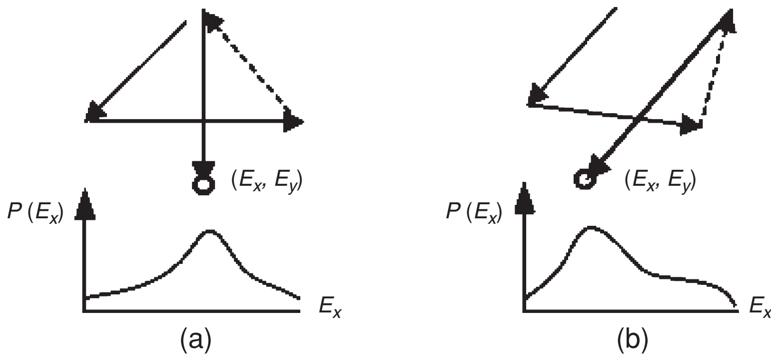

Fig. 6.2. Example of stroke relationship in the character 4. According to positions of other strokes, E_x (X position of the last stroke end point) is likely to be (a) centred in X-axis and (b) in the left-hand side of X-axis.

Relationships between strokes can be statistically defined as dependencies of positions between them; a stroke position gets influence from those of other strokes. For example, when the three strokes of the character 4 are written like Figure 6.2(a), the X position of the end point of the last stroke (E_x) is likely to be centred in X-axis. However, when they are slightly skewed clockwise like Figure 6.2(b), E_x is likely to be located in the left-hand side of X-axis.

To explicitly model strokes and their relationships have the following advantages. First, strokes are conceptual elements and their relationships are conceptually meaningful, especially in characters of oriental languages such as Korean, Chinese and Japanese. Second, their shapes are usually simple and consistently written so that they can be reliably trained with less amount of data compared with holistic character modelling approaches. Last, stroke relationships are robust against geometric variations and important for discriminating characters of similar shapes.

In spite of the advantages, strokes and their relationships have not been actively adopted in on-line handwriting recognition systems because of limitations in their modelling frameworks. The systems have mainly employed