Chapter III
Landmark-Based Shape Context for Handwritten Digit Recognition

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ABSTRACT

This chapter introduces landmark-based shape context. Standard shape context computation samples at regular interval on the contour of an object. Corner points of an object being landmarks on the contour; set of corner points is a good descriptor of shape. Landmark-based shape context is computed by sampling a reduced set of points based on such landmarks. In this chapter, an approach to recognizing handwritten digits based on shape similarity computed through landmark-based shape context is presented. Shape context based object recognition being an iterative process; the reduction in the number of sample points provides a basis for faster recognition.

INTRODUCTION

Over last three decades, character recognition has been an active research area. The potential of being used in various applications such as developing reading aid for the blind, office automation, language processing and multi-media design makes Optical Character Recognition (OCR) popular. OCR focuses on the recognition of machine printed output. The goal of OCR is automatic reading of optically sensed document text so as to translate human-readable characters to machine readable codes. OCR focuses on the recognition of machine printed output where special fonts can be used and variability between characters and digits with similar font size and font attributes is reasonably small. On the contrary, variability of handwritten characters and digits is surprisingly high. This makes handwriting recognition far more challenging.

Handwritten digit recognition is important for automating bank cheque processing, postal mail sorting, job application form sorting, and automatic scoring of tests containing multiple choice questions as well as other applications where numeral recognition is necessary. Further, with the development of miniaturized, portable and wireless equipment, *Calligraphic User Interface* based on handwriting recognition has become an essential part in the next generation of human-computer interaction (Hansmann, Merk, Nicklous, & Stober, 2001). Consequently, handwriting recognition has seen much active research in the past decade. The thrust is to push recognition rates to those near human performance (Wierer & Boston, 2007a). The ultimate objective of handwriting recognition is high-speed recognition, which has zero error rate and low rejection rate. Recognition of isolated handwritten digits continues to be of interest for the research community. Numerous approaches have been proposed for pre-processing, feature extraction, learning as well as classification. For a comprehensive survey see (Plamondon & Srihari, 2000).

Handwritten digit recognition can be classified into two categories: offline recognition and online recognition (Liu, Nakashima, Sako, & Fujisawa, 2003). Offline recognition process and recognize the user input handwritten digit based on images (the scanned images of handwritten digit). A number of methods have been proposed to solve offline recognition (Plamondon & Srihari, 2000). Offline recognition has a number of hurdles. The algorithm for image processing is complex and poses a high resource requirement. Moreover, the recognition clues available are few. For many applications, off-line handwritten recognition suffices. Inversely, the on-line recognition technology, which has emerged in recent years, uses the geometry and temporal dynamic information of the users' input (Jiang, Sun, Yuan, Zheng, & Xu, 2006). The methods for online recognition relatively pose low resource and processing requirement, and may effectively use many kinds of clues to capture users' input customs. They are effective with good user adaptation. The major issue of applying online recognition methods is how to effectively model handwritten digit and implement user adaptation.

Many systems and classification algorithms have been proposed in the past years for handwritten digit recognition. Liu et al. (2003) does a bench-marking of the different techniques in the field including major feature sets, learning algorithms and datasets. Suan and Tan (2005) present an analysis of state-of-art classifiers for recognition of handwritten digits. Most approaches involve statistically based methods, due to their relative ease of implementation as compared to semantic methods. Techniques ranging from statistical methods such as nearest neighbour classification (Aradhya, Kumar, & Noushath, 2007) and shape matching (Belongie, Malik, & Puzicha, 2002) have been applied. Machine learning techniques like neural networks (Hu, Zhu, Lv, & Zhang, 2006) and support vector machines (DeCoste & Schölkopf, 2002) have been used. Lately, hybrid (Gorgevik, 2004) as well as non-traditional classifiers (Xiu-fang, Tian and Xue-song, 2007) has been explored.

The feature description of handwritten digit has critical role in recognition. The traditional feature description of handwritten digit can be mainly categorized into two sorts: global features and structural features. The global features mainly refer using statistical methods to obtain the features such as the pixel destiny, rectangular, feature point, mathematical transform and so on. These features are hard to be extracted and the computation requirement is expensive. The structural features are the basic features about the character shape, which are extracted from the outline or skeleton of character, including the circle, the vertex, the pitch point, the arc, breaks out, hollowly, the stroke and so on. These features are suitable for syntax analysis, because they are easy to be extracted and discriminated. However, the descriptions for them are too complex.

Selection of a feature extraction method is probably the single most important factor

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