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日本語と欧米のオンライン手書き認識についての一サーベイ

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あらまし 本稿では，日本語手書き認識と欧米手書き認識の技術動向についてのサーベイを行う．特に，両者の相違点と共通点を明らかにしながら最近の成果をまとめる．両者を比較することにより，いろいろな手法の適応性や手書き認識に共通する特徴を理解することができる．また，同一の認識エンジンで日本語と欧米言語の両方の手書き文字を認識するシステムを 開発するために有益な知見を与える．

キーワード オンライン手書き認識，日本語文字認識，欧米文字認識，技術動向

A Brief Survey on the State of the Art in On-Line Handwriting Recognition for Japanese and Western Script

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Abstract This paper presents a brief overview of the state of the art in Japanese character recognition and western handwriting recognition based on the Latin alphabet. It provides an overview of recent developments with a special emphasis on differences and similarities in both fields. Comparing eastern and western handwriting recognition techniques helps to learn from different approaches and to understand the underlying common foundations of handwriting recognition. This is very important when it comes to developing integrated systems capable of recognizing both writing systems simultaneously and dealing with multi-language documents.

Key words On-Line Handwriting Recognition, Japanese Character Recognition, Western Handwriting Recognition, State of the Art.

1. Introduction

Recognition engines capable of recognizing many different writing systems will become very important in the near future. This is due to the steadily increasing popularity of pen-based interfaces in combination with new, more powerful hardware supporting pen input. The expanding international markets and booming world-wide communication will soon require recognition engines to support multi-language documents. This paper investigates the main differences and similarities of current Japanese and western handwriting recognizers to help implement recognition systems for both writing systems within a single framework. To better describe the different methods in Japanese and western handwriting recognition, the authors divided recognition into pre-processing, classification, and post-processing. Accordingly, this paper contains one section for each processing step. Many statements made in this paper are also valid for Chinese character recognition, or Asian character recognition in general, since the Japanese writing comprises a substantial subset of the Chinese character set.

2. Pre-processing

The section on pre-processing is divided into a subsection about normalizing unknown input patterns and a subsection dealing with computing features from normalized patterns.

2.1 Normalization

The main purpose of normalization is to reduce pattern variations caused by different recording hardware, noisy environments, or writer specific characteristics. By far the most important normalization in Japanese character recognition is size normalization, which is performed in virtually every Japanese character recognizer. The fact that Japanese characters are written into printed or imaginary boxes facilitates normalization. The introduction of non-linear normalizations has significantly improved the average recognition rate for Japanese characters [25], [30]. A very successful non-linear normalization method is line density equalization [30]. It expands dense sectors of the box while sparsely occupied sectors are contracted. Thus, the

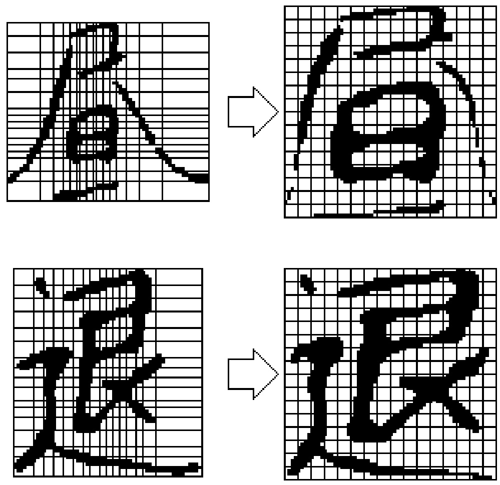

図 1 Line Density Equalization.

line density is equalized and the box is utilized more efficiently. Figure 1 shows an (off-line) Kanji character normalized with line density equalization.

Western words are written from left to right and the relation of their width and height can vary a lot. This is the main reason why western words require more elaborate normalization techniques. Moreover, it is one of the reasons why hidden Markov models, which accept input with variable length, are dominant in western handwriting recognition. A widely-used technique for normalizing size of western words is to recover the original, often imaginary, writing lines. The original writing lines are usually recovered by interpolating the local minima and maxima of trajectories ([2], [21]). Writing lines serve several purposes: First, they allow to measure the size of words and thus to normalize word patterns. Second, their rotation is a good indicator for the rotation of words. Third, baselines divide a word into distinct horizontal regions that are often used to describe the position of the pen for feature computation [2], [7]. Most western recognizers recover the baseline and the corpus line from a handwritten word pattern: The baseline is the original writing line on which a word or text was written, and the corpus line intersects the tops of lower case characters. Some western systems also recover the ascender line and the descender line [1]: The ascender line delimits the ascenders of words, and the corresponding descender line delimits the descenders of words. The size of a western word is determined by its cor-

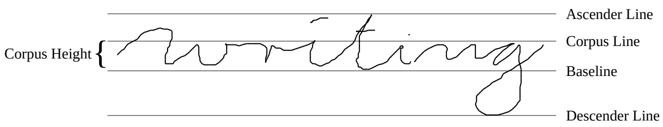

図 2　Baselines.

pus height, which is the distance between baseline and corpus line. Accordingly, a western word is size-normalized by transforming its core height to a given, fixed height. Figure 2 shows four recovered lines and the corpus height for the word "writing" as an example of western size normalization.

Other normalization techniques for western handwriting recognition which are rarely used in Japanese character recognition include interpolation with Bezier curves, smoothing, and slant correction [7]. Western words often have a slant that is characteristic for a specific writer and which, in general, is different for left-handed and right-handed persons. Slant is normalized for western words by means of a linear shearing, where the shear operator is being determined by a histogram counting the numbers of different slant angles in the trajectory [2], [7].

Western and eastern handwriting recognizer utilize similar techniques for compressing data. These techniques remove points that produce only minor modifications of the general shape of the trajectory, such as points lying on a straight line or points generated by erratic movements. The remaining points obtained after normalization and data compression are often called feature points in Japanese character recognition since they are directly utilized to compute features. Some systems compress on-line data by discarding a point from the trajectory when the directional deviation from its predecessors does not exceed a given threshold [2], [10], [28]. Other systems use the following recursive method for data compression [6], [13], [20]: The start and end point of every stroke are taken as feature points. Then, the point that is most distant from the line joining these feature points is added to the set of already existing feature points if its distance is higher than a given threshold. This process is applied recursively; eventually generating the final set of feature points.

2. 2 Feature Computation

While spectrograms are features commonly applied in speech recognition, both eastern and western handwriting recognition still lack a widely recognized and standardized set of features. Nevertheless, it is fair to classify most features utilized in western and eastern on-line handwriting recognition as simple geometrical attributes, such as distances, angles, curvatures, projections onto axes, or local directions [7]. In general, western recognizers utilizing on-line information achieve higher recognition rates than recognizers that need to rely solely on off-line information. On the other hand, on-line information is very sensitive to stroke order variations, whereas off-line information is not. This is the reason why off-line recognition can better compete with on-line recognition in Japanese character recognition: Stroke number and stroke order variations, which definitely complicate on-line recognition, are very typical of Japanese on-line characters. In western handwritings, stroke order variations are typically caused by i-dots, t-crossings, and other diacriticals whose order may vary. Many western handwriting recognizers handle diacriticals similarly: They apply simple heuristics to detect diacriticals, indicate their position in the feature vector, and finally remove them [7]. For Japanese characters, correct stroke order and stroke numbers are taught in school. In practice, however, many variations from the ideal occur and techniques for handling stroke order variations become more important than in western handwriting. The same holds for Chinese, which suffers even more from stroke order and stroke number variations than Japanese [16]. This motivates on-line recognition systems to exploit off-line information in order to achieve a higher stability against stroke order and number variations [4]. However, incorporating off-line features into an on-line recognition engine is still an open problem. On-line recognition techniques, such as hidden Markov models, require dynamic input and cannot deal with static, off-line information. Recent approaches trying to combine on-line and off-line information have therefore concentrated on augmenting on-line features with off-line features or, vice versa, adding on-line features to off-line features. For instance,

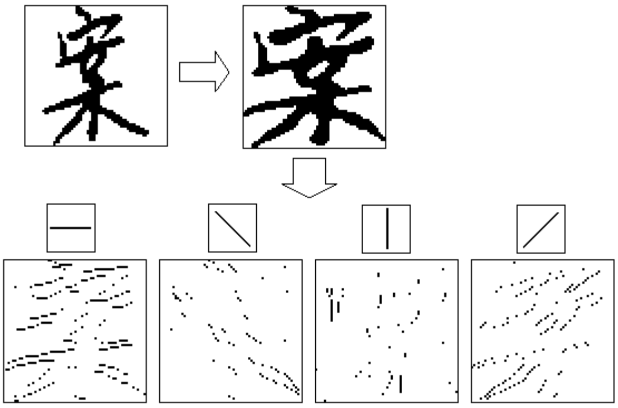

図 3　Directional Features.

Reference [7] describes off-line features termed context maps that have been added to the feature set of a western on-line handwriting recognition system. Context maps contain local, pictorial information of the trajectory at a specific time instant together with parts of the trajectory that have a high temporal distance.

An often applied technique to handle stroke order variations in Japanese character recognition are histograms. Histogram features, a term coined here for the first time, are basically statistics describing absolute or relative frequencies of feature values in handwritten trajectories. The main idea is to count the number of occurrences of a specific on-line feature value, such as directional change, and disregard the time of its occurrence. Thus, on-line features are transformed to off-line features by removing some of their dynamic information; i.e., order information. Histograms can have multiple dimensions. For instance, one frequently used histogram type first partitions the static image of a trajectory into a two-dimensional array of cells, then takes these cells as histogram slots, and finally counts the number of feature values falling into each slot [8], [17], [18]. The authors of Reference [18] present histogram features, which they call directional features, describing the direction of the contour line in the off-line image between two succeeding points on the trajectory. Figure 3 shows some typical directional features computed for a Japanese Kanji character: vertical, horizontal, diagonal and anti-diagonal directional features. A second type of histogram features introduced in Reference [18] is named direction-change features. They describe the local change in direction at each point of the trajectory, independent of time.

3. Classification

The traditional classifiers in Japanese character recognition are nearest neighbor classifiers computing the distance from an unknown input pattern to all the reference patterns stored in a database. The main reason why nearest neighbor classifiers are prevalent in Japanese character recognition is the high number of characters, which can be a major problem for other types of classifiers, in particular neural networks and hidden Markov models. Hence it is very likely that nearest neighbor classifiers will dominate the scene of Japanese character recognition in the years to come. The term “template matching” is very often used when the nearest neighbor classifier requires a 1:1 correspondence between features of two feature sets describing two distinct pattern. Many Japanese template matcher compute distances based on geometrical distances or statistical correlation [8], [17], [18]. Today, however, elastic matching techniques are dominating. Since elastic matching is based on dynamic programming techniques, it is very often called DP-matching, which is discussed in the next subsection.

3.1 DP-Matching

While DP-Matching is one of the basic tools for recognizing handwritten Japanese characters, it has moved from the classification process to the post-processing step in western handwriting recognizers, where it is embodied in the search for the Viterbi path in a hidden Markov model. Due to the significance of DP-matching, several modifications of DP-matching have been proposed to adapt it to the needs of Japanese character recognition and improve its run-time behavior. In general, the complexity of DP-matching is $O(n * m)$, where n and m are the lengths of the feature vectors matched respectively. Reference [12], however, proposes a linear-time elastic matching with high recognition rates. Several other attempts have been made during the last decade to improve the classical DP-matching and increase its effectiveness. These attempts can be classified into two different promising approaches:

The first approach extends the warping of two linear sequences of features to a two-dimensional warping of images; i.e., a pixel-to-pixel mapping between two given images [26]. Since the complexity of two-dimensional warping is significantly higher than the complexity of one-dimensional warping, efficient search techniques are applied to meet practical runtime requirements; e.g., beam search. An overview of different two-dimensional warping techniques is given in [26]. The second approach is motivated by physics; in particular, by the notions of force and motion. In general, these approaches match two patterns by representing the first as a potential field and the second as a rubber-like sequence of feature points connected by springs whose energy is described by physical equations [11], [29]. The authors in Reference [11] claim that this approach absorbs deformations of handwritten character patterns comparable to non-linear normalization. Furthermore, they show that these techniques are well-suited for parallel machines.

3. 2 Hidden Markov Models

DP-matching adopted from the speech domain had been applied to western handwriting recognition before it was replaced in the eighties by the technique of hidden Markov models (HMMs) or multi-state time-delay neural networks (MS-TDNNs), a technique closely related to HMMS [7], [19]. Thus, western handwriting recognition underwent the same development that was already observed for speech recognition. This was mainly because speech recognition techniques were frequently adopted for handwriting recognition in the western world. In fact, western handwriting recognizers are often modified speech recognizers with preprocessing adapted to the needs of handwriting [7]. However, Hidden Markov models are not a common technique in Japanese character recognition. One of the historical reasons is that HMMs are a technique for implicit segmentation; i.e., integrating segmentation and classification into one process, though segmentation is not the main problem in Japanese character recognition. Another reason is that modeling Japanese characters and training models is not straightforward due to the high complexity of Japanese characters. In particular, stroke order variations and shape variations complicate the application of HMMs. Reference [23] and [5] describe one of the few approaches that use HMMs for Japanese character recognition. This approach modifies several key features of the classic HMM approach to cope with the higher complexity of Japanese characters compared to western characters. For instance, it allows for several models for the same character and replaces the classic Baum-Welch training procedure by a non-iterative learning method to reduce complexity. Evaluations reported for the Kuchibue benchmark database have been very encouraging [14]. Today, the future role of HMMs in Japanese character recognition is an interesting and still unanswered question.

3. 3 Pattern Representation

In western handwriting recognition, dictionaries are integrated into the search for the best HMM model by utilizing an efficient tree structure in order to avoid flat search. Each node in the tree represents a HMM of an individual character, and distinguished end nodes mark word ends. The tree structure is generated by merging identical prefixes of words in the dictionary into one single node. A path from the root of the tree to an end node corresponds to an entry in the dictionary. Additionally, pruning techniques are applied to ensure real-time performance [7]. Figure 4 shows the tree structure of a western dictionary.

Due to the considerably higher complexity of Kanji characters, a similar tree structure is utilized in Japanese handwriting recognition to represent not words but single characters [15]. Kanji are composed of radicals, which are elementary building blocks that can be characters themselves, and which are generally shared by many different Kanji characters. Accordingly, Kanji characters can be represented by means of a tree structure containing radicals as its nodes. Figure 5 shows such a tree representation for a Kanji symbol with three radicals [15]. The main advantage of this structure is that learning of a new radical written in a non-standard way is simply accomplished by adding it to the appropriate node in the tree structure. Thus, the non-standard, handwritten template is automatically added to all the character classes that contain the radical.

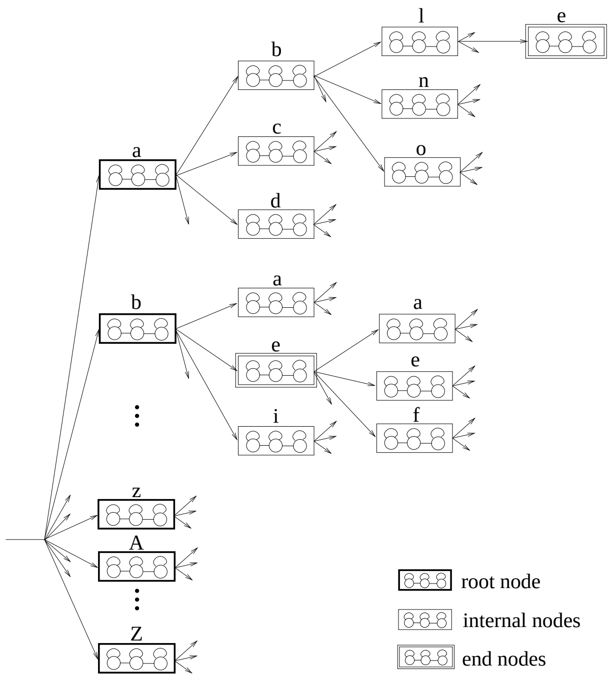

図 4 Tree representation of a western dictionary.

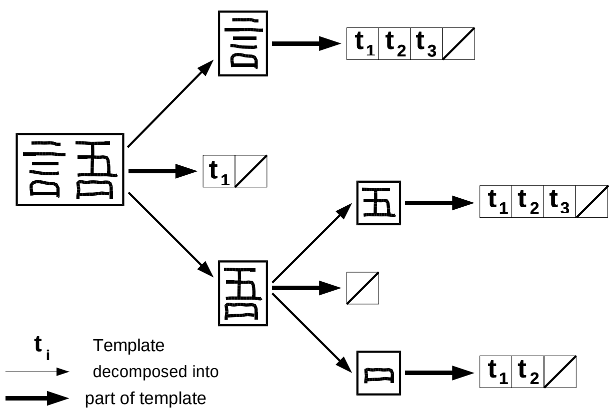

図 5 Structured Japanese character representation.

4. Post-processing

Post-processing typically deals with techniques improving recognition rates by means of additional information sources after classification. The main focus in western as well as Japanese character recognition lies traditionally on integration of syntactical knowledge and classifier combination, which are both discussed in two separate subsections here.

4. 1 Syntactical Knowledge

Though high-level grammatical information can provide valuable information for recovery of misclassifications, in practice, most western handwriting recognition systems utilize quite simple syntactical information: a dictionary in combination with n-grams, mainly bigrams or trigrams. N-grams statistics are memory-intensive and may require some techniques for data compression, in particular on small machines, such as hand-held devices. This comes along with the problem of computing reliable probabilities for very infrequent syntactical combinations when the underlying amount of data is not sufficient for a meaningful statistic. There are several techniques in the western world to address these problems [3], which could also have a beneficial effect on Japanese character recognition with its high number of character classes. However, N-grams have been applied in the Japanese speech recognition field but there is still a lack in publications merging techniques from statistical linguistics with Japanese handwriting recognition. Two publications reporting results with n-grams are [13], which shows some experiments with bigrams, and [22]. Nevertheless, it is likely that we will see more publications in the future.

Similar to the situation in western handwriting recognition, approaches utilizing higher-level syntactical knowledge have not been thoroughly investigated until now. Except for very restricted syntactical domains, it is presently unclear if we will see any general improvement of recognition rate due to *high-level* syntactical knowledge in the near future.

4. 2 Classifier Combination

Exploiting complementary information by combining different classifiers for the same classification problem has been a research field actively pursued in the pattern recognition community during the recent years [9]. Classifier combinations are of particular interest for handwriting recognition since they allow bridging the gap between on-line and off-line recognition. Stroke order and stroke number variations usually complicate on-line recognition for western, Japanese, and in particular Chinese characters. This motivates researchers to experiment with integrated on-line/off-line recognition systems that exploit valuable on-line information while off-line data guarantees robustness against stroke order and stroke number variations. The different nature of on-line and off-line data, however, complicates their combination within the classification step itself. In fact, there are currently no convincing approaches for combining on-line and off-line data directly in the classification engine. Hence most Japanese and western approaches combine both types of information either in pre-processing, mainly during feature computation, or in post-processing. Histogram features, as described above, are typical examples of combination during pre-processing. The perhaps easiest and most straightforward way of combining on-line and off-line information in post-processing is by combining independent on-line and off-line classifiers. Combination of on-line and off-line classifiers is a relatively new research topic that will surely be investigated more intensively within the next years. Some results leading to significant improved recognition rates have already been published or will be published soon [24], [27].

5. Summary

This paper presented a summary of the state of the art in Japanese character recognition with respect to techniques in western handwriting recognition. The most striking difference between on-line Japanese character recognition and western handwriting recognition lies in the classification engines themselves. While the mainstream in western handwriting recognition shifted to hidden Markov type classifiers long ago, most Japanese character recognizers still adhere to nearest neighbor classifiers. Approaches trying to utilize hidden Markov models are rare. Much effort has been spent in the western world to improve hidden Markov models and make them computational tractable. On the other hand, the same effort has been spent in Japanese character recognition for elaborate features and distance functions that are more resilient to stroke order and stroke number variations. Thus, a lot of improvements have been achieved in both western and Japanese character recognition during the last decade. But the lack of appropriate techniques dealing with the high number of Japanese characters in combination with shape, stroke order and stroke number variations have obviously deterred hidden Markov models and neural networks from gaining more influence in Japanese character recognition. Nevertheless, pre-processing and post-processing of both domains show many similarities. Due to the variable length of western words, however, western recognizer generally employ a more complex normalization.

With regard to the ultimate goal of recognizing multiple languages and supporting multi-language documents, we can summarize the following conclusion: The integration of Japanese and western classification techniques is hard to accomplish given the current state of the art. Nevertheless, the overlap of Japanese and western pre-processing as well as post-processing allows application of the same methods to both writing systems here, which in turn enables implementation of both processing steps in a single software module or hardware component.

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