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A REVIEW OF USING MACHINE LEARNING ALGORITHMS FOR IMAGE RETRIEVAL WORDS

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Abstract- The domain mismatch between queries (synthetic) and database images (handwritten) leads to poor accuracy than printed documents. One of the solutions is to represent the queries with robust features and use a model that explicitly accounts for the domain mismatch with an unsupervised method by different font selection. Information retrieval techniques such as ranking relevance, detecting stop words and controlling word forms can be extended to work with search and retrieval in the ink domain. Describe an improvement to the existing keyword retrieval (word spotting) methods by modeling imperfect word segmentation as probabilities and integrating these probabilities into the word spotting algorithm. Unconstrained handwritten document retrieval focus on information retrieval from noisy text derived from imperfect handwriting recognizers. Some method uses a novel bootstrapping mechanism to refine the OCR'ed text and uses the cleaned text for retrieval. The second method uses the uncorrected or raw OCR'ed text but modifies the standard vector space model for handling noisy text issues. The third method employs robust image features to index the documents instead of using noisy OCR'ed text. Handwritten character recognition uses the dynamic time warping (DTW) algorithm to align handwritten strokes with stored stroke templates and determine their similarity.

Keywords: Data Synthesis, Handwriting Recognition, Information Retrieval.

I. INTRODUCTION

One of the prominent applications of word image retrieval is building search engines for document images, also referred to as word spotting [1-9-16]. Manmatha et al. [9] showed that an efficient way to browse such datasets is through query-by-example. To recognize each word image, searching for a query word amounts to finding word images with sufficiently high similarity to a query image [1]. One of the objectives is to build a system that is able to query for any arbitrary word (string) when no previous training data is available that one difficulty of this method is that a model learned on synthetic samples may not be fully representative of real handwritten images. Actually, this phenomenon is known in machine learning as "concept drift", occurring when training and target sample sets have been generated by different sources [1].

Experiments of synthesizing queries demonstrate that the proposed synthesis, modeling and font weighting provide a competitive system to query for strings when no training data is available [1]. Marin et al. [15] synthesize images of pedestrians using virtual world simulators, and actually report performances close to systems trained with real images. Similarly, Schels et al. [16] use 3-D modeling soft- ware to render images of objects from different viewpoints to produce the training set for an object classifier. Wang et al. [17] use synthetic characters to learn classifiers for text detection and recognition in natural images. It is clear that the immediate application of this idea to handwritten words is difficult, especially multi-writer collections of contemporary handwriting [1].

Keyword retrieval in handwritten document images is a high- level application that relies on document analysis and recognition techniques [2]. Word spotting requires on-line matching which is time-consuming [2]. The similarity between the keyword and another word image is computed using the recognition scores, which are usually the likelihoods (probability density) of the feature space, probabilities, or some other distance-based measurements [2]. The index for fast retrieval can be built on the results of word level recognition in lexicon-driven mode [10, 11]. By improved the OCR score-based indexing method by integrating word segmentation probabilities into the retrieval similarity metric. Word spotting methods this far has assumed perfect word segmentation: word images are given by word segmentation algorithm and the ranks of word images are obtained by sorting the word recognition scores [2].

By describe a probabilistic model of word spotting that integrates word segmentation probabilities and word recognition probabilities. The word segmentation probabilities are obtained by modeling the conditional distribution of multivariate distance features of word gaps. The word recognition results are also represented by a probabilistic model. The modeling of the word recognition probabilities is obtained from the distances returned by the word recognizer [2].

In information retrieval and extraction from noisy OCR'ed text extracted from unconstrained handwritten documents [3]. Three separate research directions for tacking this problem in form of OCR correction-based retrieval methods, modified vector model-based methods and keyword spotting-based methods [3].

The primary solution to handle online handwritten data the Figure 1 [4] is to employ a handwriting recognizer (HWR) to convert the ink into text, and use the results to search and retrieve the documents [31, 32].

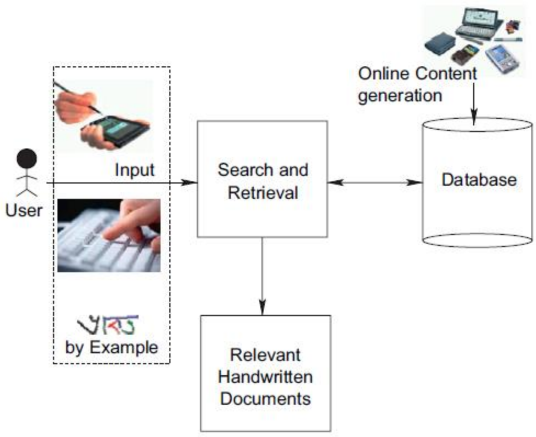

Figure 1. An effective online handwritten database should accept queries based on keyboard, pen or a sample handwritten word

Papers [5, 38] approach are inspired by the cluster generative statistical dynamic time warping (CS-DTW) technique that integrating relative positioning of strokes by referencing such a unique feature leads to better recognition.

It is necessary to pay attention to the appropriate structuring of the strokes to ease and speed up comparison between the symbols, rather than just relying on global recognition techniques that would be based on a collection of strokes [40]. Therefore, we develop a method for analyzing handwritten characters based on both the number of strokes and their spatial information [39]. Stroke consists in four main phases:

Step 1. Organize the symbols representing the same character into different groups based on the number of strokes.

Step 2. Find the spatial relation between strokes.

Step 3. Agglomerate similar strokes from a specific location in a group.

Step 4. Stroke-wise matching for recognition.

Handwritten document image retrieval by using Contour let transform, allows the retrieval of digitized handwritten document images according to writers [6]. Document image retrieval provides user with an efficient way to identify a questioned document from among a large set of known database [41]. The approach use multi-channel spatial filtering techniques to extract texture features from handwriting images [6]. There are two issues in building the proposed system in paper [6]:

• Every image in the image data base is to be represented efficiently by extracting significant features.

• Relevant images are to be retrieved using similarity measures between query and every image in the image database.

The state-of-the-art character retrieval and indexing methods only use contour points extracted from a character as a feature in the similarity retrieval [7]. The primary contributions are as follows:

1. We propose a novel probabilistic interactive retrieval method to effectively support the Chinese calligraphic characters retrieval by choosing multiple features of character.

2. We introduce a *Probabilistic Multiple-Feature-Tree* (*PMF-Tree*)-based indexing method to facilitate the interactive and efficient Chinese calligraphic characters retrieval with multiple features.

Matching of entire words in printed documents is also performed by Balasubramanian et al. (2006). In this approach, a dynamic time warping (DTW) based partial matching scheme is used to overcome the morphological differences between the words. Similar technique is used in the case of historical documents (Rath and Manmatha, 2003) where noisy handwritten document images are preprocessed into one dimensional feature sets and compared using the DTW algorithm. A Document Image Retrieval System (DIRS) based on word spotting, which has a high noise tolerance and is language independent in Figure 2 [8].

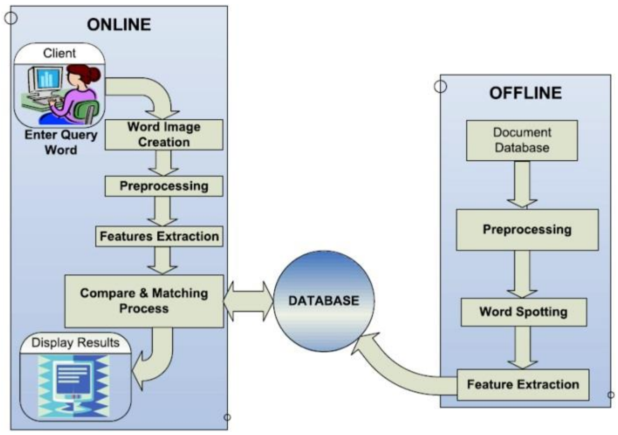

Figure 2. The overall structure of the document image retrieval system

II. BACKGROUND

Word spotting was initially proposed as an alternative approach for indexing and retrieving handwritten documents, that is one could search handwritten document images without using a handwriting recognizer In the DTW-based keyword spotting method [1, 3, 11], some preprocessing steps such as Word segmentation, Inter-word variations, bounding box of any word image, normalize the image are commonly used [2].

$$DTW(i,j)=\min\left\{\begin{array}{l}DTW(i-1,j)\\ DTW(i-1,j-1)\\ DTW(i,j-1)\end{array}\right\}+d(i,j) \quad (1)$$

where $d(i, j)$ is the square of the Euclidean distance [2]. Word spotting methods are useful when one does not have a handwriting recognizer.

On the other hand, the word matching, which is essential to word spotting, can be thought of as a prototype of word recognizer, although its performance is considerably poorer than that of a well-trained word recognizer. But handwriting recognition remains very challenging task due to the wide variations in the handwriting. Thus matching against a single template is not a robust approach [2].

A typical solution to improve the quality of information retrieval on OCR'ed text is to correct OCR errors using post-processing techniques. [26, 27] propose different methods of OCR correction for improving the information retrieval performance. Mittendorf et al. [27] propose a probabilistic model for OCR errors and use it to design a term-weighting scheme for information retrieval from document images. Jing et al. [26] build a language model that takes OCR errors into account. This model approximates an "uncorrupted" version of a particular document for efficient retrieval.

Rath et al. [28] propose an IR model that assumes independence between each term of the query for the purpose of computing its similarity with a given document. The frequency of each term is computed using the posterior probability estimated from the word image features. Howe et al. [20] use the same IR model as [28], but they do not use word recognition probabilities. Instead, they model the ranking as a Zipfian distribution where word recognition probability is inversely proportional to its rank.

There are two major classes of keyword spotting: (i) Unconstrained Keyword Spotting: also known as "recognition-based keyword spotting" that relies on an OCR (i.e. HMM) to provide probabilistic values for each keyword in the lexicon that can later be integrated into a document-level ranking score [29], (ii) Isolated Keyword Spotting: also known as "recognition free keyword spotting" that is the typical image matching task for generating the document relevance score for an input query [21].

In 2007, G. Joutel et al [42], proposed curvelets based queries for CBIR applications in handwriting collections, in this method curvelet coefficients are used as representation tool for handwriting when searching in large manuscripts databases by finding similar handwritten samples. In 2010, Liangshuo Ning et al. [35], proposed effective method for writer identification using multiscale Gaussian Markov random fields.

III. RETRIEVAL THE DOCUMENT

We assume the existence of a collection of handwritten word images. The workflow of the proposed solution is described below [1].

- *Off-line processing: only once for each collection*

1. On each image in the collection, perform a feature extraction operation.
2. Obtain the distribution of features (vocabulary) of the target collection.

- *On-line processing: for each query*

1. A user types a string Q corresponding to a word to be searched: the query.
2. Multiple images of the string Q are synthesized using a variety of pre-defined computer fonts.
3. The synthesized images undergo normalization and feature extraction operations.
4. A word model is trained which makes use both (i) of the ''synthesized'' features, and (ii) of the feature distribution (vocabulary) obtained in the off-line phase.
5. The obtained model is employed to score all the features in the collection according to the probability of each image to contain the query [1].

One of the important components of the search engine for off-line handwriting is keyword retrieval, in this context; two issues have been considered [2]:

- *A search engine for off-line handwriting*

The major challenge in retrieving handwritten documents is the difficulty of computing the term frequency (TF) due to recognition errors. This approach is to maintain an N-best list of the handwriting segmentation and recognition hypotheses, and estimate the TF using each result of the N-best list [2].

- *Word spotting using segmentation probabilities*

In word spotting using segmentation probabilities three cases are discussed; one of them is "word spotting model" [2], the other one is "estimating word segmentation probability"; Word segmentation is defined as the process of segmenting a line into words. In this word segmentation method, the word segmentation probabilities are estimated from distance-based features. The last issue is about "estimating word recognition probability"; in this system, the matching distance between a word image and a word is obtained by the word recognition algorithm of [25].

Approaches used for searching handwritten documents can be classified into recognition-based and recognition-free techniques. Depending on the application and digitization process, the data could be either word images (offline) or traces of pen motion (online). Recognition of online data has the advantage of using the additional temporal information present in the data [4].

Other approach is to represent the handwritten words using a set of features and match two words by comparing the corresponding feature vectors. This approach is referred to as *word spotting*, and is quite effective when compared to recognition based search [31, 18] for poor quality documents.

To come up with a successful search engine in the ink domain, we need to address the following issues [4]: *Variations in Handwritten Data with robust feature extraction, Scalability, Segmentation, Document Relevance Ranking, The Languages*.

The approach proposed in [4] consists of three major steps: (i) Synthesis of handwritten data from the query, (ii) Matching of the query to words in the database, and (iii) Computation of relevance scores of documents to order the results of matching.

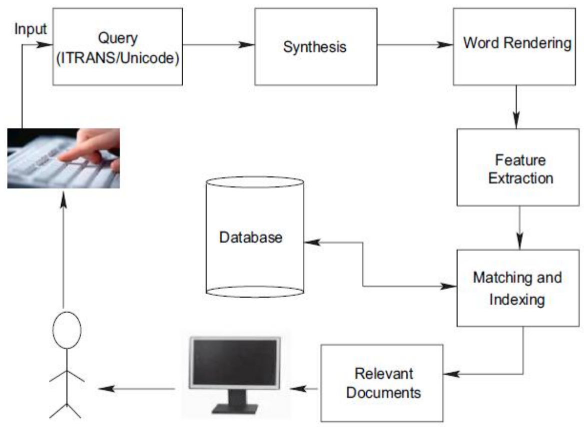

Figure 3. The entire process of synthesis and retrieval of relevant documents

The word is synthesized using the individual primitive classes, and the distribution of samples within the classes. The synthesis proceeds as follows in figure 3 [4]:

- Given a text word, create a sequence of stroke classes that constitute the handwriting equivalent of the input word. This information is learned during the training of the layout model.
- For each stroke class, we select/generate a sample stroke using the stroke model for the writer under consideration.
- The layout model is used to arrange the sample strokes to generate the final word.
- The word could be rendered in an appropriate form, depending on the application or could be passed to the next phase in applications such as retrieval and training of recognizers.

Once a handwritten word is synthesized from the query word, we use it to search the database of handwritten documents using elastic matching (DTW). The strokes are first converted into a sequence of feature vectors, extracted from each of the sample points. The feature vector consists of [4]:

(1) The direction, θ, of the tangent to the stroke curve
(2) The curvature, c, of the stroke at the sample point, and
(3) The height, h, of the sample point from the word baseline.

$$D^2 = k_\theta\left(\theta_1-\theta_2\right)^2 + k_c\left(c_1-c_2\right)^2 + k_h\left(h_1-h_2\right)^2 \qquad (2)$$

where ks are the weighting factors.

To construct the feature vectors of each image in the database, the energy and standard deviation were computed separately on each sub band and the feature vector was formed using these two parameter values and normalized [44].

We have used Canberra distance as similarity measure. If x and y are the feature vectors of the database and query image respectively, and have dimension d, then the Canberra distance is given by [6]:

$$canb(x,y) = \sum_{i=1}^{d} \frac{|x_i - y_i|}{|x_i| + |y_i|} \qquad (3)$$

IV. LEARNING

The digitiser captures a series of strokes during pen movement as soon as it starts to move over the tablet. A string of coordinates (pen-tip positions) from pen-down to pen-up events represents a stroke. Along the pen trajectory, the initial pen-tip position represents the first coordinate of the particular stroke. Similarly, the last point is taken as soon as pen-up event takes place. Depending on the user and/or writing style, a same symbol can be written with a varying number of strokes [5].

Many authors demonstrate the use and importance of normalization [36, 37]. Because of variable size of writing strokes, it is necessary to transform a complete symbol into a standard window.

Appropriate feature selection can greatly decrease the workload and simplify the subsequent design process of the classifier. Features should contain sufficient information to distinguish between classes, be insensitive to irrelevant variability of the input, allow efficient computation of discriminant functions and be able to limit the amount of training data required [43].

V. CONCLUSIONS

The three key elements of some systems are robust features, SC-HMM modeling, and unsupervised font selection all the three elements contribute to reduce the concept drift which is caused by the asymmetry in modeling real handwritten words using synthetic images. Using the image-to-image matching-based approaches use the word recognition distances to improve the word matching accuracy. Although the recognition-based approach shows the advantage over the image-to-image matching methods. Information retrieval from handwritten documents is a challenging task primarily due to lower word recognition rates in the case of unconstrained handwritten documents when compared to machine-printed document images. In the other approach uses handwriting synthesis to do matching in the ink domain as opposed to the use of a recognizer. The other approach is based on the observations of the handwriting of different writer is visually distinctive and global approach based on texture analysis has been adopted. Features were extracted from handwriting images using Contour let transform technique. Some system makes use of document image processing techniques, in order to extract powerful features for description of the word images.

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