Noname manuscript No.
(will be inserted by the editor)

Large Scale Document Image Retrieval by Automatic Word Annotation

Pramod Sankar K. · R. Manmatha · C. V. Jawahar

Received: date / Accepted: date

Abstract In this paper, we present a practical and scalable retrieval framework for large-scale document image collections, for an Indian language script that does not have a robust OCR. OCR-based methods face difficulties in character segmentation and recognition, especially for the complex Indian language scripts. We realize that character recognition is only an intermediate step towards actually labeling words. Hence we re-pose the problem as one of directly performing word annotation. This new approach has better recognition performance, as well as easier segmentation requirements. However, the number of classes in word annotation is much larger than those for character recognition, making such a classification scheme expensive to train and test. To address this issue, we present a novel framework that replaces naive classification with a carefully designed mixture of indexing and classification schemes. This enables us to build a search system over a large collection of 1000 books of Telugu, consisting of 120K document images or 36M individual words. This is the largest searchable document image collection for a script without an OCR, that we are aware of. Our retrieval system performs significantly well with a mean average precision of 0.8.

Pramod Sankar K.
Xerox Research Center India
Bengaluru, India.
E-mail: pramod.kompalli@xerox.com

R. Manmatha
Multi-media Indexing and Retrieval group, Dept. of Computer Science, University of Massachusetts, Amherst, USA.
E-mail: manmatha@cs.umass.edu

C. V. Jawahar
Center for Visual Information Technology
IIIT-Hyderabad, India.
E-mail: jawahar@iiit.ac.in

Keywords Image Retrieval · Automatic Annotation · Document Images · OCR-free annotation

1 Introduction

Traditionally, digital libraries of scanned English books are made searchable by converting images to text using an optical character recognizer (OCR). Example projects include Google Books [1], Internet Archive [2] and Universal Digital Library (UDL) [3]. However, for Indian language scripts, there are no robust OCR engines available, as yet [4]. While there is active research on building OCR engines for Indian languages [4], their performance is not yet good enough for use. The fundamental challenges in building an accurate Indic-OCR are: an extended character set, complex script layout [5], conjoined vowel/consonant modifiers for each consonant (see Figure 1), etc. Additionally, degradations such as cuts and merges have a more pronounced effect (than on English) with regards to character and component segmentation. Finally, with a digital-library-scale dataset, the framework enabling retrieval needs to be efficient and scalable.

In this paper, our goal is to build a searchable library of printed books in Indian languages such as *Telugu*. We overcome many of the issues with Indian language character recognition, by re-posing the problem to one of *word-annotation*. By focusing on recognizing words, instead of characters, better character disambiguation is possible as well as difficult character segmentation is avoided. The scalability of this approach is achieved by proposing an efficient indexing based classification scheme. The specific contributions of our paper include:

1. A novel direction in building document retrieval systems based on word-annotation [6]; which is distinct from existing approaches.
2. A unique framework to scale recognition systems to large scale test collections, by avoiding repetitive classification of similar features [7]. This results in an improvement in annotation complexity from $O(N_1 \cdot N_2)$ to $O(logN_1 \cdot logN_2 \cdot K^2)$, where N_1, N_2 are the sizes of training and test datasets and K is the branching factor of the cluster hierarchy. Consequently, a tremendous speed-up of more than 2000× is obtained over traditional approaches.
3. A thorough evaluation of features and indexing schemes for the task of word-recognition, over a challenging real-world dataset [8] created by us.
4. The largest collection of Indic document images, 120K from 1000 books, made searchable at the word-level. A significant retrieval performance with a mean Average Precision of *0.8*, was achieved.

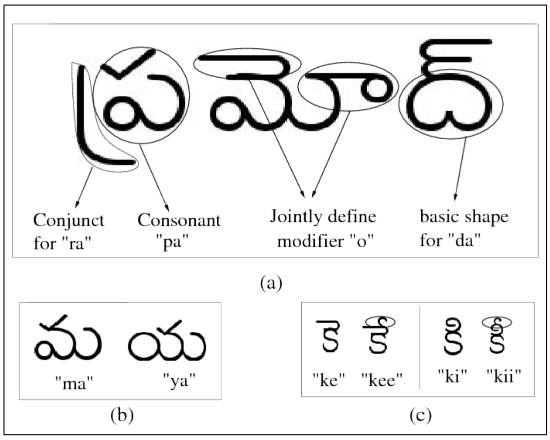


Fig. 1 Examples demonstrating the subtleties of the Telugu script. In (a) the consonant modifier is shown to be displaced from the consonant in different ways (b) the two characters *ma* and *ya* are distinguished only by the relative size of the circle (c) the small stroke at the top changes the vowel that modifies the consonant

The rest of the paper is organized as follows. In the following section, we outline the datasets that we work with. In Section 2, we discuss the previous work towards document image retrieval and we shall elaborate on why previous methods are not adequate to address our problem. We present our new solution direction in Section 3, and detail the processes involved in our framework in Section 4 and Section 5. Especially in Section 5, we outline a scheme for scaling our approach to large collections. We analyze the subtleties of our approach in Section 6, and present experimental details and results in Section 7. We compare this work with other similar previous work in Section 8 and conclude in Section 9.

1.1 Datasets

Our datasets come from document images of printed Telugu books from the Digital Library of India [9]. The collection has a variety of print quality, font and style; at varying levels of ink and page degradation. We shall refer to three sets of data in this paper:

Test Data: Our *Test* data consists of 1000 books, including many classical poetic, prose and fiction works in the language of Telugu - a language with 75 million speakers. The *Test* dataset amounts to 120K document images with 36 million word-images. This is the largest Indic dataset ever attempted for a document retrieval system. This is the dataset that we would like to build a retrieval system for, as a consequence of this work. There is a significant variation in the fonts, typeset styles and print quality in the dataset. Varying levels of degradations, such as cuts, merges, salt-and-pepper noise etc. are also present in the data. Figure 2 shows this variation for one word across the collection.

Validation Data: This is a hand-labeled groundtruth dataset of 33,000 word-images, belonging to 1000 distinct words. Each of these word-images is labeled with the corresponding text label. The number of occurrences of each label in the groundtruth dataset varies from 5 to 500. The size of the word-images range from 30×30 to 500×300 pixels. We shall use the *Validation* data to optimize the settings of our framework. The *Validation* dataset, which we call IIIT-H Telugu Word Dataset, is available for download from [8].

Labeled/Training Data: The *Training* data is a set of 33 books consisting of 3000 document images. Unlike the *Validation* data that consists of 33,000 accurately labeled word-images, the training data is a much larger set of word-images with a slightly erroneous labeling (about 80% accuracy). The labeling is obtained by *aligning* page-level transcriptions to their corresponding word-images. This was achieved by performing a *text-driven segmentation* of the document image. From the text we are aware of the number of lines in the page, number of words in each line and the (approximate) number of characters in each word. This information can be used to drive the page segmentation.

The process begins by performing line-segmentation of the document image. If the number of lines from the segmentation is less than the number of lines in the text, it means two text lines have been erroneously merged by the segmentation algorithm. This often happens because of overlapping ink pixels between the two lines,

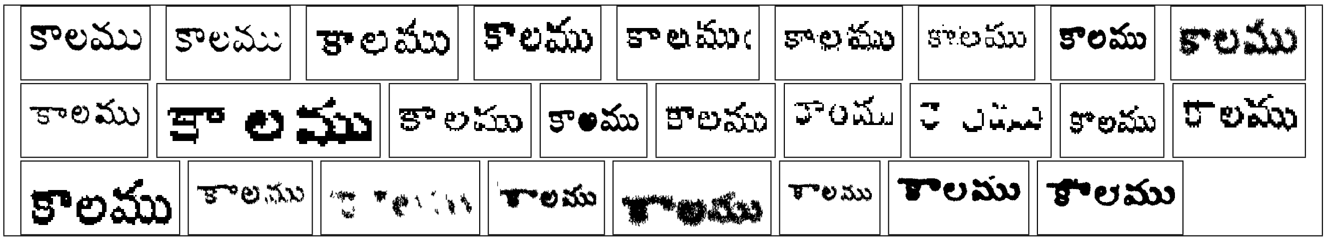
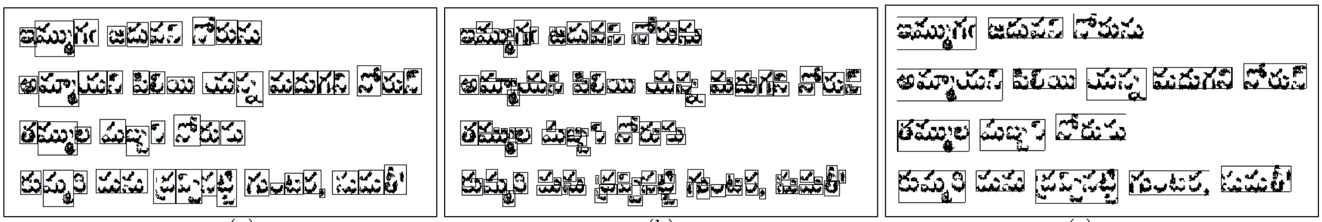


Fig. 2 Multiple instances of a single word *kaalamu* from the book dataset. Notice the large variations in the font, and the large amount of degradations in the words.



(a) (b) (c)

Fig. 3 (a) Example segment from a typical document image of our collection. Notice the considerable degradations, cuts, merges etc. in the passage. The groundtruth segmentation of characters is given as bounding boxes. (b) The connected-components of the segment in (a). One can observe the over segmentation of characters due to degradations. An OCR would not be able to recognize the characters in this situation. (c) Segmentation of the image at the word level. The effect of the degradations is much less severe in this case. We propose the matching of word-images in lieu of recognizing the characters.

due to the presence of consonant-conjuncts (see Figure 1).To correct this, the tallest lines are split until the number of lines match between the image and the text. On the other hand, if the number of lines from segmentation is more than those in text, it indicates that some lines were split by the segmentation. This is corrected by merging the smallest lines together. In the second step, each line is similarly segmented into words depending on the known number of words in the given line. Labeled exemplars for the keywords are obtained from this dataset.

2 Previous Work

Early document retrieval addressed the problem of document retrieval as a whole. Such work uses document level features or local features that collectively represent the document image [10,11]. An application of such work was applied for document tracking on a camera-based desk [12]. However, the shortcoming of whole-document retrieval is that users typically prefer to query and retrieve documents at content-level, more specifically with *words* as queries, a natural extension of web-search.

There have been two major approaches in literature towards building content-level retrieval systems. The first is a recognition-based approach involving the building of an Optical Character Recognizer (OCR) along with its post-processing modules. The other is the recognition-free *Word-Spotting* approach.

2.1 OCR

OCRs have had a long history, and surveys can be found in [13,14]. OCRs begin by segmenting the document image to connected components, each of which is considered as an isolated character. These components are represented using features such as patch-based, PCA, LDA, or other statistical features. The classifiers used to recognize characters have evolved over time from Neural Networks [15,16] to Support Vector Machines (SVM) [17]. Since SVMs are mostly suitable for two-class classification problems, a chaining architecture such as a directed acyclic graph is used to combine multiple classifiers [18]. Errors in classification are typically corrected using post-processing based on character error models [19], dictionaries [20] or statistical language models [15,21]. OCRs such as the Byblos system [22, 21] use HMMs to encode the n-gram statistics towards refining character labels. However, such methods inherently use gradient based features, which we shall show (in Section 7.1) are not reliable in the presence of severe degradations present in our data.

In the case of Indic OCRs, despite significant efforts [4], their performance is not comparable to that of English. The major road-blocks towards building Indic OCRs are:

- An extended character set, almost 5 times that of English, requiring the classifier architectures to scale to a much larger number of classes.

- A complex style of writing, where each character is a conjoint of a consonant and a vowel, making it difficult to segment the individual components for subsequent recognition. Some examples are shown in Figure 1 (a).
- A number of similar-looking character pairs, distinguished by very subtle differences, see Figure 1 (b) & (c). This calls for very strong classifiers which are both hard to train and expensive to test.
- A large lexicon that is almost 10x that of English, making language models challenging to build [23].

Moreover, a poor OCR performance translates to unacceptable word-level accuracies. Typical character recognition accuracies over document images similar to our collections are less than 90%. Assuming an average word length of 6, the word recognition accuracy would be $(0.90)^6$, or only 53%. Retrieval from such erroneous recognition results would result in poor precision and recall.

2.2 Word-Spotting

As an alternative to OCR, a number of authors have proposed techniques that avoid the use of character recognition. One such approach is based on character shape codes for word detection [24]. A set of 5 character shape codes encode each connected component, which is prone to errors from component segmentation and degradations. A few shape coding works avoid character segmentation, by proposing novel features such as stroke coding [25], topological shapes and character extremum points [26]. However, these techniques are limited by the shape-code vocabulary and are typically not invariant to font and style variations (for e.g. italics).

The more popular recognition-free approach is called *word-spotting*, where word-images are holistically represented in a visual feature space and matched with the queries in the feature space itself. Queries are either given as word-image examples or are synthetically generated [7, 27]. Features proposed for representing words include profiles [28], Gradient-based binary features [29], HoG [30] or shape-context [31]. In most cases, the features used to represent the word-images are of non-uniform length, depending on the word-image's width. With variable length features, word-images are matched using Dynamic Time Warping (DTW) [28, 32]. Apart from DTW, matching techniques using HMMs [33] (that needed to be pre-trained) and Hough transform of distance matrix images [34] were proposed. More recently, BLSTM neural networks [35, 36] have been used to obtain a pseudo-character representation, which is then matched with the query using edit distance. In the case of historical documents, a segmentation-free word spotting was presented [37] where features are extracted on blocks of the document images, which are then matched with the query. Word-spotting approaches have been extended to retrieve/recognize from hand-written documents as well [38–40].

The more successful DTW based approach is computationally intensive, with an estimated query time of 416 days for searching a single query within our test collection of 36M words. A suggested approach to overcome the impractical retrieval times is to perform an offline-indexing using either clustering [28], or with Locality Sensitive Hashing [41]. However, indexing the features from large datasets (about 210 GB for 1000 books), is infeasible even on advanced computers. Also, some of the features such as the split-style HoG feature [30] are of a very high dimension, making it unsuitable to manage for large collections. Further, word-spotting systems can only be queried-by-example, while users prefer text querying. Text querying requires that text labels be provided to the word images. In [42], such labels were obtained over handwritten documents, by applying a relevance model learnt from transcribed documents.

2.3 Dataset Size Comparisons

With regards to scalability aspects, much of the previous work has been restricted to laboratory settings or small document collections. Due to the unavailability of a large labeled corpus, most of the experiments were done only on a limited number of pages [43]. The UNLV dataset [44] evaluated OCRs on a set of 2000 pages. In word-spotting techniques, the test set sizes range from a few tens of images [45–48, 28] to a few books [49]. The largest handwritten collection of about 1000 pages comes from George Washington's diary consisting [42]. One of our previous papers [7] was the first to build a retrieval system over a collection of 500 (printed) Telugu books, consisting of 75,000 document images. In this paper, we shall extend our previous work to a much larger collection, while significantly boosting performance and slashing computational requirements.

3 Our Approach

At the outset, we realize that in order to replicate web-search characteristics and performance on document images, a text-based retrieval system is the best option. A textual representation also allows for many breakthroughs in text retrieval, summarization and translation to be applied to document images in the future.

Aspect	OCR	Word Spotting (DTW based)	Our Approach
Text querying	Yes	No	Yes
Retrieval time	Instantaneous	Time-consuming	Instantaneous
Accuracy	Poor for Indian languages	Acceptable	State-of-the-art
Degradation	Serious Effects in Segmentation	Lesser Effects in Segmentation	Lesser Effects in Segmentation
Font Sensitivity	Limited to Training Fonts	Robust to Font Variations	Robust to Font Variations
Data Scalability	Scalable	Not Scalable	Scalable
Vocabulary Coverage	Limited by Post-processing	Limited by Manual Annotation	Limited by Training data

Table 1 A comparison of our approach with the most popular techniques available for document retrieval. Our approach has multiple advantages over either approach taken alone.

Since OCRs are not the effective approach to obtain the corresponding text, we re-pose the problem to one of *word-annotation*.

3.1 Towards Annotating Words

The move from character to word labeling is motivated by these observations:

1. Word-images contain a lot more information, than individual characters. This contextual information present within a word helps in better disambiguation between word-images, which would otherwise result in errors when recognised at character level. For example, in the word "image", the "m" could easily be misclassified as "in" or "ni" if there is a cut. However, the word as a whole will most likely match with the right label.
2. Segmentation of the document to words is much more reliable than segmenting to characters and components. Component segmentation is highly inaccurate, especially in the presence of complex scripts, and degradations. For the example document image given in Figure 3 (a), the component segmentation over-segments the characters, as can be seen in Figure 3 (b). On the other hand, the word segmentation shown in Figure 3 (c) is very accurate.
3. For the purpose of retrieval, character/component level labeling is *not* required. Character recognition is only an intermediary step towards performing word annotation. Another advantage with recognizing words is that dictionary based verification could be performed as part of the recognition step itself, hence avoiding an additional post-processing step.

Further, not all words in document images are informative towards indexing them. Since it only suffices to label those words that are useful from a search perspective, our process is one of *annotation* instead of full-fledged recognition. The comparison of our approach with OCR and word-spotting is given in Table 1. Our approach is distinct yet combines the advantages of both these directions into a new framework.

3.2 Problem Setting

We begin with two inputs: i) a set of test document images $D_1, D_2, ..., D_N$, each document D_i consisting of word-images $W_i^1, W_i^2, ..., W_i^{n_i}$, and ii) a set of words (in text) forming the vocabulary-of-interest, $V_1, V_2, ..., V_M$. The word-image set W_i^j and the text-vocabulary V_k are drawn from different datasets, hence there is no knowledge if a given word-image W_i^j corresponds to a text label V_k. The word-annotation problem now boils down to finding the appropriate word V_k, if it exists, for each word W_i^j. Without any loss of generality, the same problem can also be posed as one of finding all the words W_i^j that correspond to the given word V_k in the vocabulary. Such a labeling will directly result in a search index over the documents. Since, the task of finding datum corresponding to a given keyword, is the conceptual opposite of the traditional annotation scheme, we call such a process *Reverse Annotation* [7].

Algorithm 1 Word Annotation Framework

Offline Phase
- Training Phase
  - Identify appropriate features and parameters from *Validation* dataset
  - Learn classifiers for word-annotation using labeled data from *Training* dataset
- Test Phase
  - Index/Cluster *Test* dataset
  - Classify one (or k) data-points per cluster against learnt classifiers
  - Annotate all points of cluster, with appropriate label

Index Building
- Index word-images based on their text-labels
- Rank the points within an index

Online Phase
- Obtain textual query from user
- Retrieve ranked lists for each query word
- Re-rank documents using TF-IDF

A conceptual overview of our framework is presented in Algorithm 1. We shall now proceed to elaborate on the design choices for each of the steps in this algorithm. For each Section, we indicate the corresponding step of the algorithm in parentheses.

4 Classifier Design for Word Annotation (*Offline Phase - Training*)

4.1 Identifying the Vocabulary (Classes)

In retrieval systems, the choice of vocabulary $\{V_k\}$, that can be searched for is an important design criterion. Practical text search engines do not index (and answer) all possible queries, since such an index could span all possible unique words in the language. For example, search engines such as Lemur [50], Galago [51], etc do not index strings made up of special characters. The goal of building a search index, is to optimize the percentage of queries that can be answered and documents that can be retrieved. Similarly in our work, we could limit the vocabulary size to optimize the query-document coverage.

The distribution of the keywords in our training dataset is shown in Figure 4. It follows the well known Zipf's law [52], that states that the frequency of any word is inversely proportional to its rank in the frequency table. At the head of the distribution, we find what are called stop-words, such as $\{the, a, an, and, ...\}$. Stop-words do not contribute to the retrieval task, hence it would only be a waste of index space. The distribution also has a *long-tail*, consisting of a large number of words that occur only a few times.

Consequently, we design the vocabulary-of-interest V_k, such that a large percentage of documents are indexed and large percentage of queries are answered. We first remove stop-words, by thresholding on the inverse document frequency (IDF) measure. The IDF is defined as $log(\frac{|D|}{|d:t \in d|})$, where $|D|$ is the number of documents in the collection and the denominator is the number of documents containing the given term. We consider all the words that occur in one-tenth of the document collection, as stop words. This corresponds to an IDF threshold of 2.3. Rare-words are removed by thresholding the term frequency (TF) at 10. Our vocabulary-of-interest consists of 100K words.

4.2 Building the Classifier

When we re-pose the problem from character recognition to word annotation, the number of classes that need to be learnt, expands from the character set (of about 300) to the size of the vocabulary (100K in our case). Such a class size is quite large compared to typical machine learning problems addressed in the literature [53, 54]. This results in two issues: i) the classifiers need to be designed to scale to the large number of classes and ii) significant amount of reliable training data is required to learn the classifiers.

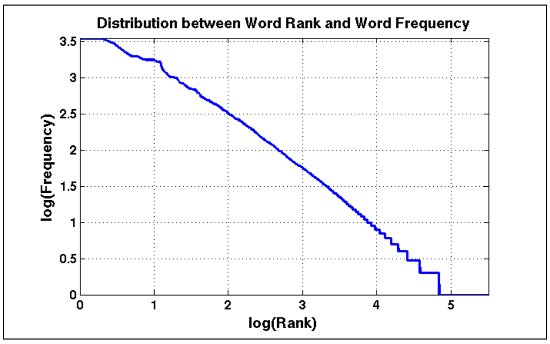


Fig. 4 The distribution between the word rank and word frequency from our training dataset. As expected, the distribution follows Zipf's law, an exponential relationship between the frequency of a word and its rank based on the frequency. An ideal Zipf's distribution follows a straight line on the log-log plot between rank and frequency.

In picking a classifier, apart from high performance, the major requirement is that the classifier scheme be scalable to huge test collections. In traditional machine learning work, the focus has been on improving classification accuracy and/or the training times. We believe however, that for our problem, scalability in the test phase is more important. Accordingly, we examine two distinct classifier schemes: i) Nearest Neighbor and ii) Support Vector Machines (SVM), to measure suitability of each for word-image annotation.

SVMs are inherently two-class classifiers. Multi-class classification with SVMs is performed by either building $|C|$ one-vs-rest classifiers, or $|C| \cdot |C-1|/2$ one-vs-one classifiers. Each data point is classified as belonging to the classifier with biggest margin (for one-vs-rest), or the class that is selected by most classifiers (for one-vs-one). The major issue with one-vs-rest classifiers is the lack of a reliable mechanism to combine classifier scores, especially when the internal parameters of the individual SVMs depend on the data or class distributions. The second approach is obviously prohibitive to train and test for our problem where $|C|$ is 100K. Each data point would then have to be classified by $5 \cdot 10^9$ SVMs, which would be infeasible. Moreover, SVMs require large amounts of training data to learn the classifier accurately.

We experimentally verify this intuition over our validation dataset of 32K word-images belonging to 1000 classes. SVMs were built for each of the 1000 classes using half the validation data as training set and the other half for testing. The classifier with the maximum score is chosen as the class for the test point. Results from this experiment are shown in Table 2. As can be seen,

Classifier	Distance/Kernel	Accuracy	Training Time	Test Time
SVM	Linear Kernel	58%	8 min	21 Hours
SVM	Polynomial Kernel	46.8%	9 min	23 Hours
Nearest-Neighbor	DTW	81%	0	75 Hours
Nearest-Neighbor	Euclidean	78.6%	0	4 Hours
Nearest-Neighbor	Manhattan	**82.8%**	0	3.5 Hours

Table 2 Word Recognition accuracy using SVMs and Nearest Neighbor classifiers, using Profile features over our validation dataset consisting of 32K words from 1000 word classes; 16K used for training and 16K for testing. SVMs are easily out-performed by a Nearest Neighbor classifier, both in accuracy and classification time.

SVMs perform much poorer than a Nearest Neighbor classifier using the same features. Apart from performance, SVMs are also slow to train and test, due to the 1000 classifiers (one for each word) that needed to be learned and classified against.

5 Annotation on a Large Scale (*Offline Phase - Testing*)

The challenge in the testing phase is scalability of the classifier scheme to large test collections. For example, the NN classifier requires about 0.77 second per test sample. The time required to classify our test dataset against all 100K classifiers would require about 90 years of compute time, which is clearly not the optimal classification scheme. We shall address the scalability challenge by proposing a novel mechanism based on this unique premise:

One need not classify every given data-point. Classification can be re-used across similar data.

In a typical machine learning scheme, each test case is considered isolated and classified independent of each other. With such a naive classification, the complexity of classification is $O(N_{Test} \cdot O(C))$, where N_{Test} is the number of data points to classify and $O(C)$ is the inherent complexity of the classifier for the classes of interest. However, we observe that this is quite un-necessary, since the test samples follow an inherent distribution. A number of samples are either repetitions or near-duplicates of other samples. Consider a scenario where one could identify if a data point has the same (or similar) features as another data point. In such a case, only one of these features needs to be classified, and the classification result can be re-used for the other point. Such a scheme would be effective under the following fairly generic conditions:

1. The size of the test data is much greater than the number of classes ($N_{Test} >> |C|$).
2. The test samples follow a distribution that is not arbitrary, but closely reflects the distribution of training data. This ensures that the priors learnt by the classifiers are valid for the test data as well.
3. Smoothness Assumption: If two points x_1, x_2 are close, then so should their corresponding classifier outputs y_1, y_2. Consequently, if $y_1 \approx y_2$, then the two points can be assigned the same label $V_1 = V_2$.

For the case of document images, we find that all these assumptions are valid. It is quite obvious that the list of classes in the word-annotation is limited by the known vocabulary size of the language. The data, however, that can be indexed with such a vocabulary could be limitless. It is also known that the test data follows a Zipf's distribution, similar to the training set. With Zipf's distribution, a large amount of the mass is present in a small percentage of the distribution. This is an ideal candidate to re-use classification scores, when multiple instances of the same data are seen often. The third condition only requires that the matching scheme be robust to noise. In cases where condition 3 is false, it would imply that two features that are close in the given feature space, actually belong to different categories. This would mean that the features and/or the distance measure are highly sensitive to noise, and hence not the right setting to learn the classifier. As we shall show in Section 7, our features and classifiers are indeed robust, hence satisfying condition 3.

Given the validity of the above assumptions, as a consequence, we now make the "Cluster Assumption": if points $\{x_1, x_2, ..., x_n\}$ all belong to the same cluster, they are likely to be of the same class. More precisely, for a given point x_i, and its cluster centroid $C(x_i)$, for some reasonable τ:

$$y(x_i) = y(C(x_i)) \quad if \quad d(x_i, C(x_i)) < \tau$$

where $y(.)$ is the label for the given data point.

Thus, if we were able to cluster the word-images, such that the maximum radius of the cluster is less than a certain threshold τ, then it would suffice to classify only one point, namely the centroid of the cluster. We could then propagate the class label of the centroid to the rest of the cluster, without having to classify every single point.

In the case of word-images, the centroid is typically a very clean representative candidate of the various instances of word-image occurrences across the data collection. Thus, the classification of the centroid is much more accurate than classification of those points at the fringe of the cluster.

5.1 Clustering Training Data

With the clustering scheme, the computational cost of using a classifier reduces from $O(N_{Test} \cdot O(C))$ to $O(K \cdot O(C))$. Here K is the number of clusters in the test data, K is typically a small multiple of the number of classes, C. In the specific case of Nearest Neighbor classifiers, a further cost saving could be achieved. We observe that the keyword-exemplars themselves are not totally isolated in the feature space. While multiple exemplars of the same word would be clustered together at the lower levels of the cluster hierarchy, at a higher level similar words that vary in only a few characters would be found together. Thus, *keyword-exemplars can also be clustered* based on the similarity in their representative features. If the exemplar set is larger than the size of M, we built forests of keyword exemplars too.

Matching Clusters Through Trees: Imagine we are given a pair of trees T_D and T_K, one belonging to the unlabeled word-image dataset and another from the keyword exemplar set. The problem of word-annotation is now the task of matching the clusters at the leaf node of T_D, to the specific exemplar belonging to T_K. Unlike an exhaustive matching between all the leaf nodes between the pair of trees, we could exploit the paths between the leaf nodes to prune out unsuccessful matches beforehand. We assume that two clusters will not match at a lower level, unless their parent nodes match. This is a fair assumption, even in cases where the clusters in the two trees partition the feature space differently. This technique is depicted in Figure 5. Using this method, the complexity of matching exemplars with features is now reduced to $O(logN_1 \cdot logN_2 \cdot B^2)$, instead of $O(N_1 \cdot N_2)$ for a regular Nearest Neighbor (NN) classifier.

5.2 Efficient Clustering Schemes

In the previous section, we introduced the concept of clustering for avoiding repeated classification of similar points. However, the process of clustering itself is expensive, typically requiring $O(N_{Test}.K)$ time, where K is the number of clusters. Another limitation of the K-Means clustering algorithm is the necessity to fix K beforehand. If K is less than the number of unique words in the collection, it would mean that some of the clusters would have different words in them. A larger K reduces the chance that images corresponding to different words will be part of the same cluster. The trade-off is that a larger K will lead to multiple clusters for the same word. However, this would increase the compute time. We shall look at two approaches to perform this process in reasonable time.

Hierarchical K-Means (HKM) is a way to approximate K-Means fast. The idea [55] is that a small number of clusters - say B - are created at the top level, B is known as the branching factor. In the next step, each of these B clusters is expanded to B more clusters giving B^2 clusters at the second level. This process is repeated up to a certain depth D so that B^D clusters or leaf nodes are formed at depth D, typically $D = log_B(N_{Test})$. To build the entire HKM tree requires $O(N_{Test} \cdot K \cdot D)$ time while K-Means would require $O(N_{Test} \cdot K^D)$. For a million data points, the speed-up is from 31 yrs for K-Means to 13 hrs for HKM. Once the HKM tree is built, given a new point it takes $B \cdot D$ comparisons to find out which cluster it belongs to, unlike traditional K-Means which would take B^D comparisons. For example, if $B = 10$, $D = 6$ then there are one million leaf nodes. While K-Means requires 10^6 comparisons while HKM only needs 60.

Another approach to speeding up clustering is by using approximate nearest neighbor search. In K-Means, the most expensive step is the mapping of data to the closest provisional centroid, at each iteration. This is essentially the problem of nearest neighbor matching, which can be approximated using indexing schemes such as Locality Sensitive Hashing or Random Forest of KD-Trees.

Locality Sensitive Hashing: In Locality Sensitive Hashing [56] (LSH), data points are projected onto random subspaces, such as a line or hyperplane. The projected subspace is divided into spatial bins; each point is assigned to the bin it falls into. The assumption is that points close to each other in a high dimension space will most likely fall into the same bin in the low-dimensional projection. Multiple such hash functions are generally used to collect additional evidence to determine NNs. A feature vector x, is mapped onto a set of integers by each hash function $h_{a,b}(x)$. For a pre-defined bin-width w, the hash function $h_{a,b}$ is given by,

$$h_{a,b}(x) = \lfloor \frac{a \cdot x + b}{w} \rfloor.$$

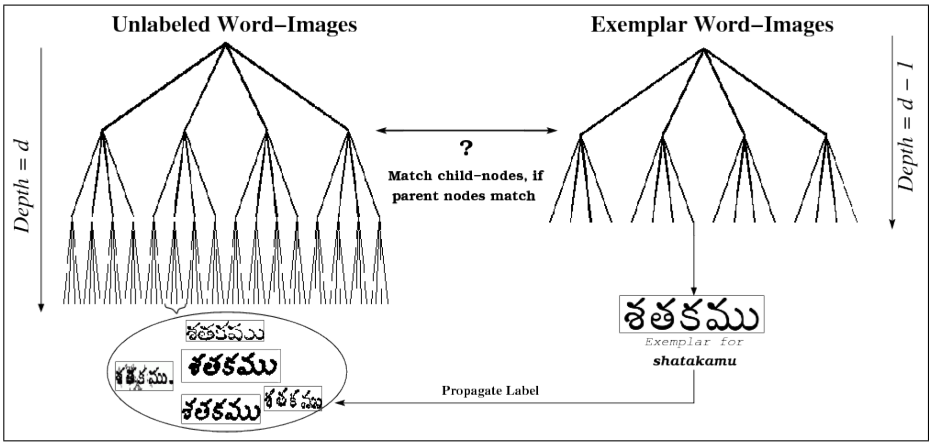


Fig. 5 Word Annotation by efficient comparison of hierarchical clusters of labeled and unlabeled word-images. For brevity, only one tree is shown for the index of each dataset. In reality, a forest of trees is used to index the exemplar and test datasets.

Feature vectors that are close in the feature space are expected to fall into the same hash bin. As a corollary, data points that have the same hash value over multiple hash functions are expected (but not necessary) to be close in the feature space. Following this, for each test feature, the hashed values in the same bins as the test feature are returned as the approx-NNs.

Random Forest of KD-Trees: Another approach to addressing the approximate NN problem uses a random forest of KD-Trees [57]. A KD-Tree partitions the feature space with axis-parallel hyperplanes. The algorithm splits the data in half at each level of the tree on the dimension for which the data exhibits the greatest variance. The tree is looked up for NNs, by comparing the query with the bin-boundary at each level of the tree(s). Building a KD-tree from n points takes $O(n\ log\ n)$ time, by using a linear median finding algorithm. Inserting a new point takes $O(log\ n)$ and querying for nearest neighbors takes $O(n^{1-1/k}+m)$, where k is the dimension of the KD-Tree and m is the number of nearest neighbors. The algorithm [57] first traverses the KD-tree and adds the unexplored branches in each node along the path to a priority queue. It then finds the closest center in the priority queue to the given query, and uses this node to restart the traversal. The process is stopped when a predetermined number of nodes are visited. Further, a Random Forest of multiple KD-Trees is used to improve the ANN evidence for better clustering quality. When building a random forest, the split dimension is chosen randomly from the first D dimensions on which data has the greatest variance. Multiple trees define an overlapping split of the feature-space. These trees are looked up for NNs, by comparing the query with the bin-boundary at each level of the tree(s). By using a voting scheme over the different trees, we obtain very reliable clusters.

Incremental Indexing Irrespective of the indexing scheme used to speedup clustering, memory limitations are easy to breach in large datasets. To begin with, the features for our test dataset (36M word-images) occupy a diskspace of 210 GB, which cannot be loaded in one instance on a single machine. Further, all indexing schemes have large memory overheads, where memory is traded for speedup. For example, the storage complexity of LSH is of the order $O(N_{Test}.|H|)$, n being the number of features hashed and H is the set of hash functions. Since the optimal $|H|$ depends on the size of the dataset N_{Test}, the memory required for a large dataset could be more than what modern computers can handle [58]. We address this issue, by dividing the dataset into subsets, say M of them, and build separate indexes over each subset. The size of the subset is determined by the maximum number of features that can be indexed in one instance. Once the indexes are built, the approximate nearest neighbors are obtained by looking up each subset against the index of every other subset (including itself). Thus, the process of clustering would involve M indexing steps, and M^2 lookup steps.

5.3 Indexing of Document Images (*Indexing Phase*)

At the end of the word-annotation procedure, we have an index of the word-images against the keywords. However, the index does not lend itself to ranking the word-images for retrieval purposes, since the associations in the index are binary. The ranking is based on a probability that consists of two parts. The first part measures the quality of labeling of a cluster (i.e. its centroid) with the given keyword-exemplar. The second term measures the association of the word-images to the cluster.

Let us assume that the word-image t_i is the centroid of a certain cluster, and the set of word-images in this cluster are represented by $\{t_i^1, t_i^2, ..., t_i^n\}$. If the closest keyword to this cluster is given as V_k, then the probability that word-image t_i^j matches this keyword is given as:

$$p(V_k|t_i^j) = \frac{s(V_k||t_i)}{\sum_i \sum_k s(V_k||t_i)} \times \frac{s(t_i||t_i^j)}{\sum_j s(t_i||t_i^j)} \quad (1)$$

where $s(x||y)$ is a similarity measure (inverse of a distance measure). Since we assign a single label to each cluster, for $V_{k'} \neq V_k$, $p(V_{k'}|t_i^j) = 0$.

The denominator of the first term involves the summation over all keywords and all clusters (a modified version of that used in [7]). While computing the denominator is expensive, we observe that it remains a constant for all word-image and keyword cluster pairs. For ranking purposes we can ignore the denominator while computing the score. The computation of the score can thus be performed only between the pairs of exemplar and test-set clusters which match in the word-image annotation phase, hence preserving the computational advantages of the framework.

5.4 Ranking of Retrieved Documents (*Online Phase*)

Given the ranking of word-images against the query, the relevant documents are ranked using a function similar to the Term Frequency/Inverse Document Frequency (TF-IDF) measure. In the ranking function, the sum over the number of words is replaced with their probabilities given by Equation 1. TF measures the importance of the keyword for the image, and is normalized by the document length to avoid bias to longer documents. The document length is replaced by the sum of the probability scores of all the words within the document, against their respective keywords. This scheme ignores the words that are not labeled in the annotation step. For the query-word V_k, the TF for a document D_i containing word-images $\{W_i^j\}$, is defined as,

$$TF(D_i|V_k) = \frac{\sum_j p(V_k|W_i^j)}{\sum_{j,k} p(V_k|W_i^j)}. \quad (2)$$

where the denominator is a sum of all the scores between the word-images and their matched keywords.

When the search query consists of multiple words, the relative importance of the words in the query is an important distinguishing factor during ranking. This is estimated by the *inverse document frequency* (IDF) measure, which indicates the overall importance of the given keyword in the entire collection. It is basically the logarithm of the total number of documents over those containing the given term. The modified IDF measure is defined as

$$IDF(V_k) = log \frac{|D|}{1 + \sum_i \delta(\sum_j p(V_k|W_i^j))}. \quad (3)$$

The δ function ensures that multiple word-occurrences within a document are counted only once:

$$\delta(x) = \begin{cases} 1 : x > 0 \\ 0 : x = 0 \end{cases} \quad (4)$$

The $TF \times IDF$ provides the final ranking of documents for the given query-words.

6 Analysis of the Solution

Effect of Clustering Errors: Clustering of data is crucial to our solution. It is possible that some of the clusters are not "pure". This could be because of multiple reasons: i) the words are inherently similar looking, ii) degradations cause the words to appear similar or iii) the cluster centers are initialized in the intra-class region in the feature space. One of the solutions that we suggest to improve cluster purity is by allowing multiple clusters for each word in the vocabulary. Ideally, if the vocabulary size $|V|$ is known, the number of clusters "K" should be equal to the number of unique words. Using $K < |V|$ will inevitably result in clustering errors. When the vocabulary size is unknown, it is suggested to use a large K, thereby allowing multiple clusters for some of the words, but not constraining the different words to fall into a limited number of clusters.

The effect of cluster size on the purity of the clustering was analysed over the validation dataset (described in 1.1). The dataset consists of 32K word images belonging to a vocabulary size of 1000. The precision, recall and F-measure of various cluster sizes is shown in Figure 6. As can be seen, when $K < |V|$, the precision of the clusters is very poor. The precision improves as K increases, with the most precision of 1.0 reached when each data point is a separate cluster. However, the recall value of the clustering would tend to 0.0 in such a case. Consequently, we choose an operating point where there is sufficient trade-off between precision and recall as defined by the F-measure. From our experiments, we observe that an acceptable F-measure was when the number of clusters was around *5 times* the vocabulary size. We use this observation while building the clusters over our test data.

Further, instead of creating a single cluster tree over the data, multiple such trees, are generated for the same

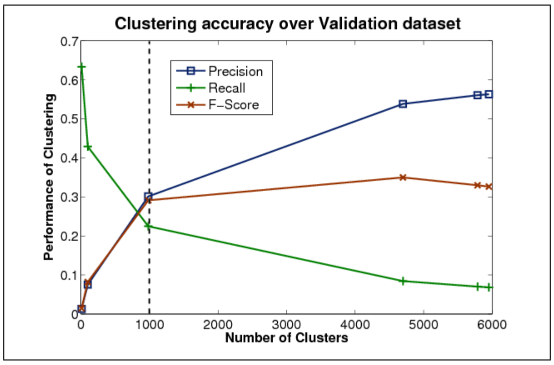


Fig. 6 Clustering accuracy across number of clusters, over the Validation dataset (32K word-images, 1000 unique-words). The precision increases while the recall drops with increasing K. The F-measure is used to identify the optimal trade-off between precision and recall.

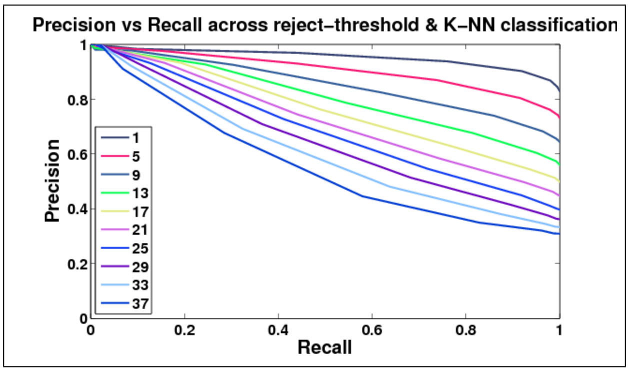


Fig. 7 Performance of classification across reject-threshold and the $k-NN$ settings of the classifier, over the $Validation$ dataset. The 1-NN classifier works best, and we choose a reject threshold that gives a recall of atleast 80%. The precision at this operating point is more than 95%.

set of data, and a voting scheme is used to identify clusters that are reliable. In cases where errors remain in the cluster, we do end up with errors in their labeling. However, as we shall see in Section 7.2, the drop in recognition performance due to the clustering scheme is less than 3%, while providing tremendous speed-up.

Refuse to Label & Soft Labeling: In our problem definition, we restrict ourselves to a subset of the vocabulary, which allows us to focus more on labeling those words that would be useful for retrieval. Consequently, there would be many word-image clusters, that do not belong to the vocabulary of interest. In order to avoid labeling such clusters, we assign labels only if the classifier score for the closest keyword, is greater than a pre-defined threshold. The reject threshold is chosen by analyzing the effect of the threshold on the precision of classification and the accept-rate (or recall) of the classification.

The effect of the threshold over classification of the validation dataset is shown in Figure 7. As observed from the plot for 1-NN classification, the precision is high across various recall points. We choose the threshold where recall is atleast 0.8, i.e. atleast 80% of the points are assigned a suitable label. At this threshold, the accuracy of classification is more than 95%. Further, we observe that with the $k-NN$ classifier, better performance is observed with smaller k. The 1-NN classifier gives the best recognition accuracy across different k.

On the other hand, instead of assigning a single label to a cluster (or word-image), one could also label the word-images with multiple matching keywords, along with storing their match score. This would partially address the presence of similar-looking but distinct word-images within a cluster. By assigning the top-m word labels to a given cluster, one could improve recall for rare words that are not large enough to form a distinct cluster in the feature space. This would require a small change in the computation of probabilities of Equation 1, by computing probabilities over all valid V_k for a given cluster centroid t_i. The results in this paper were obtained without assigning soft labels, owing to memory constraints on storing and accessing the large indexes. Soft labeling could also be employed by allowing each word-image to belong to multiple clusters, drawing from success of such methods in object retrieval [59]. Some of the advantages of soft-clustering are implicitly obtained by building multiple cluster trees. Explicit soft-labeling, however, would hurt the speedup that we gain from assigning word-images to a single cluster.

Effect of Segmentation Errors: Though the segmentation requirements at the word-level are much easier to handle than character segmentation, errors occur occasionally in word segmentation. This could be due to overlapping ink pixels across multiple lines of text, or due to insufficient inter-word spaces. In our framework we match words as a whole, refraining from partial matching (using DTW), to save on computational expense. This results in words with segmentation errors to be rejected or mis-labeled in the annotation phase.

Scaling to Larger Collection: Once the index is built over a 1000 books, one can examine the prospect of adding more books to the searchable collection. Given another 1000 books, the same process can be repeated: i) divide the collection into M subsets each, ii) build hierarchical clusters over each of the M subsets and iii) match these trees with those built over the *Training* set. It can be inferred that the process is *linear* in collection sizes, thus the framework is scalable to bigger digital libraries.

7 Experimental Results

In this section, we shall evaluate various choices available for building our framework. The evaluation of features (Section 7.1), indexing schemes (Section 7.2 and labeled data quantity (Section 7.3) is based on the ground-truthed validation dataset (described in 1.1). The performance of our approach on the $Test$ dataset is presented in Section 7.4.

7.1 Feature Evaluation

The features that represent the word-images are required to be robust to variations in font, style and degradations. We examine three holistic features that have been popularly used in the document recognition community:

– Profile features
– Scale Invariant Feature Transform (SIFT) + Bag-of-Words
– Pyramid Histogram of Oriented Gradients (PHOG)

Profile Features: Profile features were popularized by Rath and Manmatha [60], where these features were used to represent words from handwritten documents. The profile features we extract include (see [60] for more details):

– The Projection Profile is the number of ink pixels in each column.
– Upper and Lower Profile measures the number of background pixels between the word and the word-boundary
– Transition Profile is calculated as number of ink-background transitions per column.

Each profile is a vector whose size is the same as the width of the word. The dimensionality of the feature, therefore, varies with the word used. Such variable-length features are typically matched using Dynamic Time Warping (DTW) [60,61]. However, owing to the computational cost of DTW, an alternative fixed length representation was obtained by scaling the word images to a canonical size before extracting the Profiles.

SIFT + BoW: An alternative to Profile features is to use a point-based representation for the word-images. SIFT [62] (Scale Invariant Feature Transform) has proved to be very successful in many computer vision tasks. The SIFT operator contains two parts - an interest point detector and a descriptor. The interest point detector is based on the difference between multi-scale Gaussians of the given image. The descriptor is a histogram of oriented gradients. The scale-invariance property of SIFT and its high repeatability across various affine transformations makes it a good candidate to be used in document images [45].

Feature	Distance	Accuracy	Time
Profile Features	DTW	81%	75 Hours
Profiles (Scaled)	Euclidean	78.6%	4 Hours
Profiles (Scaled)	Manhattan	$\boxed{82.8\%}$	3.5 Hours
SIFT (1000)	Euclidean	26.4%	4 Hours
SIFT (100K)	Euclidean	8%	11 Hours
PHOG (100)	Euclidean	35.2%	30 Minutes
PHOG (1000)	Euclidean	41.8%	4 Hours
PHOG (100K)	Euclidean	14.1%	11 Hours

Table 3 Word Recognition accuracy across various features and matching schemes. The number of *visterms* used for SIFT and PHOG are mentioned in parentheses. Profile features work the best, while SIFT and PHOG are seriously affected by the degradations (cuts and merges) present in the images

Pairwise matching of SIFT features between word images is time consuming. To alleviate this, the features are mapped to a unique ID, called the *visterm*. Images can now be matched by counting the overlap between corresponding visterms. The visterms are obtained by vector quantizing the SIFT features using K-Means clustering. Each feature in a word-image is represented as the index of the cluster visterm. The word-image is then represented as a histogram of the occurrences of each visterm. Given this representation, two words are compared by finding the distance between the corresponding histogram feature vectors.

PHOG + BoW: Unlike SIFT, which is a sparse detector, we also examine a dense representation with similar descriptors such as Histograms of oriented gradients (HoG) [63]. We use a pyramidal HoG [64] to represent each word-image. To compute this feature, a fixed size window is moved across the word-image, and at each instance a HoG descriptor is computed. Once the entire word-image is scanned by the window, the window size is doubled and the process repeated, till the window size exceeds the word-image's size. The set of extracted features are vector quantized, and the word-image is represented as a histogram of the occurrences of each visterm.

Performance of the features is reported in Table 3, which shows that the best performing feature was the scaled-profiles with L1 distance matching (83%). Thus, our setting outperforms the state-of-the-art DTW matching of Profile features (81 %), which also has the additional disadvantage of high time complexity. The recognition over the validation dataset set alone takes around 75 hours with DTW, as opposed to 3.5 hours using scaled-profiles. Further, the gradient features - SIFT and PHOG - perform rather poorly in spite of their

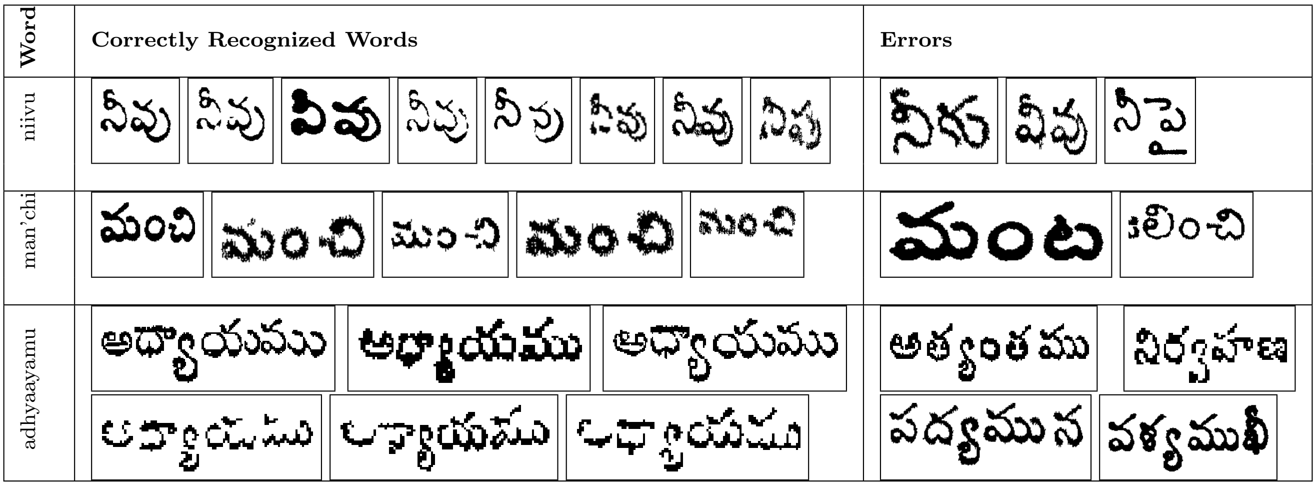


Fig. 8 Example recognition results from the book collection. Notice the severe degradations in some of the correctly recognized words. We recognize these words where OCR easily fails. Most of the errors are due to similar looking words (or part of), or due to erroneous labeled data.

great success with generic vision tasks. This is not surprising, given the large amount of degradations present in our document images which *drastically affect the oriented gradients*. The profile features are thus more robust to degradations.

Example results from our annotation module are given in Figure 8. As we observe, a large number of words are correctly recognized in spite of heavy degradations and font variations. We benefit from the presence of similar looking labeled exemplars in the training set. It is important to note that the best performing Telugu OCR does poorly on the kind of degraded words that we successfully label.

In cases where our procedure fails, the features are unable to distinguish between different words. For example, consider the results for the word *man'chi* (row 2) of Figure 8. The first erroneous word is *man'ta*, which differs in the last (third) character. Notice the strong similarity between the first correct and the first erroneous word. In the second erroneous example, the second half of the word (*lin'chi*) matches with the label, and is hence misclassified. We also observe some errors due to erroneously labeled training images.

7.2 Performance of Indexing Schemes

Our next experiment evaluates the performance of various indexing schemes. The evaluation results from this experiment are given in Table 4. The features used here are scaled-profiles, and the distance measure is either Euclidean or Manhattan. As can be seen, the indexing schemes give a large speedup of over 500 times as compared to a brute-force NN classifier. The small loss in accuracy of 2.5%, from the use of indexing is an acceptable trade-off for such a speedup. The best performing scheme is the composite of KD-Tree and HKM, used with the L1-Norm. For KDTrees and HKM, we use the FLANN software provided by [57].

Matching Scheme	Distance	Accuracy	Time
NN Classifier	Euclidean	78.6%	4 hours
NN Classifier	Manhattan	82.8%	3.5 hours
HKM ($B = 8$)	Euclidean	76.5%	22s
HKM ($B = 32$)	Euclidean	75.1%	32s
HKM ($B = 8$)	Manhattan	77.5%	22s
HKM ($B = 32$)	Manhattan	77.2%	32s
KD-Tree ($T = 8$)	Euclidean	69.4%	28s
KD-Tree ($T = 32$)	Euclidean	72.9%	41s
KD-Tree ($T = 8$)	Manhattan	71.5%	24s
KD-Tree ($T = 32$)	Manhattan	75.2%	45s
LSH	Euclidean	78.3%	18 m 14s
LSH	Manhattan	80.1%	16 m 38s
HKM + KD-Tree	Euclidean	76.8%	37s
HKM + KD-Tree	Manhattan	80.3%	37s

Table 4 Word Recognition accuracy using various indexing schemes. For HKM B is the branching factor, and T is the number of KD-Trees used for indexing. Features used in this evaluation are scaled-profiles. The drop in performance due to the indexing scheme, is about 2.5%, which is easily compensated for by more than 340x speedup in classification.

7.3 Effect of Labeled Data Quantity

Another aspect that we evaluate, is what amount of labeled word-images, is required to reliably recognize unlabeled word-images. Unlike a 50:50 split that was used in the experiments of Sections 7.1, 7.2, we shall vary the split proportions here. We stick to the scaled-profiles and the Euclidean distance based NN classifier

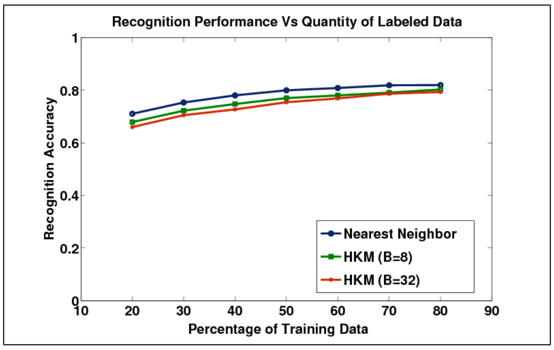


Fig. 9 Graph of % Training data Vs Recognition performance

with HKM index. The recognition accuracy for different percentage of training data is shown in Figure 9. For the NN classifier, it can be seen that for a labeled dataset of as small as 20%, the recognition performance is a respectable 71%. The performance improves with additional data until it tapers around 76.5% (for the 50:50 split), after which there is no significant improvement. For the HKM approach with $B = 8$, we can achieve 70% accuracy with just 30% of the data.

7.4 Word Retrieval Performance on Test Data

Popular information retrieval evaluation measures such as precision, recall and f-measure, assume that the number of relevant documents is known in the collection. However, given our massive collection, it is impossible for us to obtain the exact recall value for the queries. To evaluate our word-retrieval performance, we propose using an approximate estimate of average precision. We manually label the top-1000 retrieved results, as relevant or irrelevant to the query. By labeling the search results, we are effectively evaluating results over the entire collection; instead of evaluating over a small groundtruthed subset, like in other previous work. The number of true-positives in the top-1000 are considered as an approximation of the true recall. Hence, when the top-1000 retrieved results are considered the recall value is always 1. This is very similar to the evaluation performed in the TREC web retrieval challenge [65]. We evaluate the precision across various values for this approximate recall. The Precision-Recall curve averaged over 100 queries is shown in Figure 10.

The Average Precision (AP) is computed as the average of precision at each relevant retrieval for the given query. The Mean Average Precision (mAP) is the mean of the AP for multiple queries. We obtained the labels for about 100 queries, from which the mAP was calculated to be **0.8**. A few qualitative examples of document retrieval are shown in Figure 11. The query was "vishvadaabhiraama vinuraveima", a characteristic phrase used by a famous Telugu poet called *Vemana*. Among the 1000 books in the collection, the relevant books and pages containing or discussing these poems were retrieved.

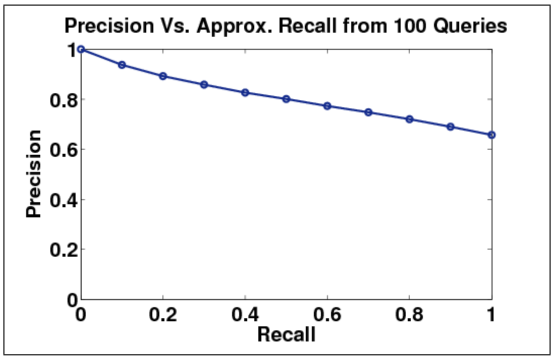


Fig. 10 Precision-Recall curve evaluated on the top-1000 retrieved results for 100 queries. The mean Average Precision of the retrieval system is *0.8*.

Aspect of the Pipeline	Time Taken
Segmentation	42 Hours
Feature Extraction	2140 Hours
Feature file pre-processing	3.5 Hours
Indexing and Lookup	445 Hours
Post-processing	58 Hours
Total	2688.5 hours

Table 5 Time consumed by each stage of the pipeline; and the total time for making 1000 books searchable. On average, the time required per book is less than 3 hours. Our approach is linearly scalable, hence similar computing times would be required to index the next 1000 books.

7.5 Computational Time

The superiority of our method is further highlighted by the reasonable time it takes for enabling search. The times taken by each step of the pipeline are given in Table 5. The total compute time for processing the 1000 books was close to 2700 Hours, or only 2.7 hours per book.

8 Comparison with Previous Work

In this paper, we extend some of the ideas that we previously presented (to a limited extent) in Pramod and Jawahar [7] and in Pramod *et al.* [6]. In Pramod *et al.* [6], approximate nearest neighbor techniques were used to match exemplar word-images with a set of unlabeled word images. This approach was used to build a collection OCR over a smaller set of 33 books (the same set of 33 books was used to generate the training data

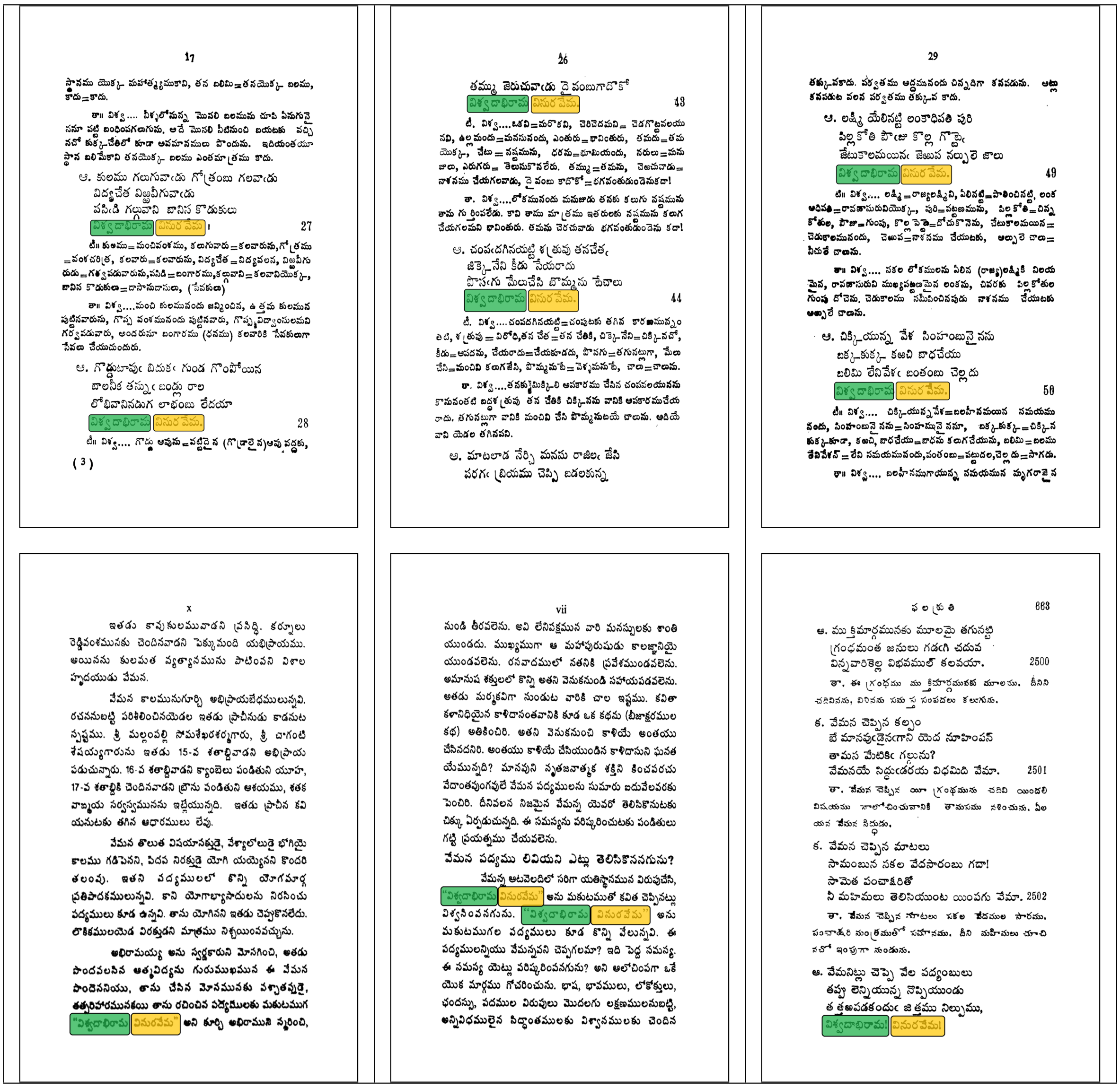


Fig. 11 Document images containing or discussing the poems written by *Vemana* were retrieved by querying for a characteristic phrase used by the poet.

for this paper). On the other hand, in [7], word-images from the document-images were matched against synthetic labeled exemplars that were obtained by font-rendering with a single canonical font. The word-images and exemplars were represented using the profile features [66], which were matched with a Dynamic Time Warping (DTW) based distance measure. Due to this distance measure, clustering of word-images was needed to be performed using Hierarchical agglomerative clustering. The approach was demonstrated over a collection of 500 books consisting of 75,000 document images in the Telugu script. However, the clustering was computationally intensive, requiring close to 21,000 hours of computing (30 machines running for 30 days). This was thus, not scalable to much larger collections; doubling the dataset would have required twice the computing time. Though the complexity of scaling is linear in collection size, the constant is very large, making it quickly unacceptable.

In this paper, we have modified the techniques, by which we reduced the clustering and annotation process to less than 500 hours, a speedup of more than *85* times. This was achieved by representing word-images using fixed-length representations, which allowed the use of simpler distance metrics. The clustering is speeded up using approximate-NN techniques such as Locality Sensitive Hashing, KDTrees and Hierarchical K-Means. Further, the synthetic labeled exemplars are replaced by training samples obtained from document images. Due to the similarity in appearance with word-images, the new training exemplars significantly improved the labeling accuracy.

9 Conclusions

In this work, we have presented a successful and scalable framework to enable retrieval from a large collection of document images. Our approach is applicable to many languages for which robust OCRs are not available. In future work, we could explore methods to allow indexing of a much larger vocabulary, in the absence of training data. This would enable retrieving for rare-word queries, especially nouns. Further, we could consider the possibility of applying similar techniques for other visual recognition tasks.

Acknowledgments

This work was supported in part by the Ministry of Communications and Information Technology, Govt. of India. R. Manmatha was supported in part by the Center for Intelligent Information Retrieval and by the National Science Foundation grant #IIS-0910884. Any opinions, findings and conclusions or recommendations expressed in this material are the authors and do not necessarily reflect those of the sponsors.

References

1. Google Books at: http://books.google.com.
2. Internet Archive at: http://www.archive.org.
3. Universal Library at: http://www.ulib.org/.
4. Govindaraju, V., Setlur, S., eds.: Guide to OCR for Indic Scripts. Springer (2009)
5. Kumar, K.S.S., Kumar, S., Jawahar, C.V.: On segmentation of documents in complex scripts. In: Proc. ICDAR. (2007) 1243–1247
6. Pramod Sankar K., Jawahar, C.V., Manmatha, R.: Nearest Neighbor based Collection OCR. In: Proc. DAS. (2010)
7. Pramod Sankar, K., Jawahar, C.V.: Probabilistic reverse annotation for large scale image retrieval. In: Proc. CVPR. (2007)
8. IIIT-H Telugu Word Recognition Dataset, available at: http://cvit.iiit.ac.in/index.php?page=resources.
9. Digital Library of India at: http://dli.iiit.ac.in.
10. Doermann, D.: The indexing and retrieval of document images: a survey. Computer Vision and Image Understanding **70** (1998) 287–298
11. Marinai, S.: A survey of document image retrieval in digital libraries. In: Colloque International Francophone sur l'Ecrit et le Document (CIFED). (2006) 193–198
12. Kim, J., Seitz, S.M., Agrawala, M.: Video-based document tracking: Unifying your physical and electronic desktops. In: Proc. UIST. (2004) 99–107
13. Nagy, G.: At the frontiers of OCR. IEEE **80** (1992) 1093–1100
14. Pal, U., Chaudhuri, B.: Indian script character recognition: A survey. Pattern Recognition **37(9)** (2004) 1887–1899
15. Tong, X., Evans, D.A.: A statistical approach to automatic ocr error correction in context. In: Proc. WVLC. (1996) 88–10
16. Francesconi, E., Gori, M., Marinai, S., Soda, G.: A serial combination of connectionist-based classifiers for OCR. IJDAR **3** (2001) 160–168
17. Byun, H., Lee, S.W.: Applications of support vector machines for pattern recognition: A survey. In: Proceedings of the First International Workshop on Pattern Recognition with Support Vector Machines. (2002) 213–236
18. Jawahar, C.V., Kumar, M.P., Ravikiran, S.S.: A bilingual OCR system for hindi-telugu documents and its applications. In: Proc ICDAR. (2003) 408–413
19. Kahan, S., Pavlidis, T., Baird, H.S.: On the recognition of printed character of any font and size. IEEE PAMI **9**(2) (1987) 274–288
20. Lehal, G.S., Singh, C., Lehal, R.: A shape based post processor for gurumukhi OCR. In: Proc. ICDAR. (2001) 1105–1109
21. Natarajan, P., MacRostie, E., Decerbo, M.: The BBN Byblos Hindi OCR System. Guide to OCR for Indic Scripts (2009) 173–180
22. Lu, Z., Schwartz, R., Natarajan, P., Bazzi, I., Makhoul, J.: Advances in the bbn byblos ocr system. In: Proc. ICDAR. (1999) 337–340
23. Bharati, A., Rao, P., Sangal, R., Bendre, S.M.: Basic statistical analaysis of corpus and cross comparision. In: Proc. ICON. (2002)
24. Spitz, A.L.: Using character shape codes for word spotting in document images. Shape, Structure and Pattern Recognition (1995) 382–389
25. Li, L., Lu, S.J., Tan, C.L.: A fast keyword-spotting technique. In: Proc. ICDAR. (2007) 68–72
26. Lu, S., Li, L., Tan, C.L.: Document image retrieval through word shape coding. IEEE PAMI **30**(11) (2008) 1913–1918
27. Kesidis, A.L., Galiotou, E., Gatos, B., Pratikakis, I.: A word spotting framework for historical machine-printed documents. IJDAR **14** (2011) 131–144
28. Rath, T.M., Manmatha, R.: Word spotting for historical documents. IJDAR **9**(2-4) (2007) 139–152
29. Zhang, B., Srihari, S.N., Huang, C.: Word image retrieval using binary features. In: DRR'04. (2004) 45–53
30. Terasawa, K., Tanaka, Y.: Slit style hog feature for document image word spotting. In: Proc. ICDAR. (2009) 116–120
31. Llados, J., Sanchez, G.: Indexing historical documents by word shape signatures. In: Proc. ICDAR. (2007) 362–366
32. Meshesha, M., Jawahar, C.V.: Matching word images for content-based retrieval from printed document images. IJDAR (2008) 29–38
33. Kuo, S.S., Agazzi, O.E.: Keyword spotting in poorly printed documents using pseudo 2-d hidden markov models. IEEE PAMI **16** (1994) 842–848
34. Nishi, H., Kimura, Y., Iguchi, R.: A new word spotting framework using hough transform of distance matrix images. In: Proc. IMECS. (2010) 280–285
35. Frinken, V., Fischer, A., Bunke, H., Manmatha, R.: Adapting BLSTM neural network based keyword spotting trained on modern data to historical documents. In: Proc. ICFHR. (2010) 352–357
36. Jain, R., Frinken, V., Jawahar, C.V., Manmatha, R.: BLSTM Neural Network based Word Retrieval for Hindi Documents. In: Proc. ICDAR. (2011) 83–87
37. Gatos, B., Pratikakis, I.: Segmentation-free word spotting in historical printed documents. In: Proc. ICDAR. (2009) 271–275

38. Madhvanath, S., Govindaraju, V.: The role of holistic paradigms in handwritten word recognition. IEEE PAMI **23** (2001) 149–164
39. Srihari, S., Srinivasan, H., Babu, P., Bhole, C.: Handwritten arabic word spotting using the cedarabic document analysis system. In: Proc. Symposium on Document Image Understanding Technology (SDIUT). (2005) 123–132
40. Adamek, T., O'Connor, N.E., Smeaton, A.F.: Word matching using single closed contours for indexing handwritten historical documents. IJDAR **9**(2-4) (2007) 153–165
41. Kumar, A., Jawahar, C.V., Manmatha, R.: Efficient search in document image collections. In: Proc. ACCV. (2007) 586–595
42. Rath, T., Manmatha, R., Lavrenko, V.: A search engine for historical manuscript images. In: Proc. SIGIR. (2004) 369–376
43. Atul Negi, Chakravarthy Bhagvati, B.K.: An ocr system for telugu. In: Proc. ICDAR. (2001) 1110–1114
44. Rice, S.V., Jenkins, F.R., Nartker, T.A.: The fifth annual test of ocr accuracy. Technical report, UNLV (1996)
45. Ataer, E., Duygulu, P.: Matching Ottoman words: An image retrieval approach to historical document indexing. In: Proc. CIVR. (2007) 341–347
46. Xiu, P., Baird, H.S.: Scaling up whole-book recognition. In: Proc. ICDAR. (2009) 698–702
47. Konidaris, T., Gatos, B., Ntzios, K., Pratikakis, I., Theodoridis, S., Perantonis, S.J.: Keyword-guided word spotting in historical printed documents with synthetic data and user feedback. IJDAR (2007) 167–177
48. Lavrenko, V., Rath, T.M., Manmatha, R.: Holistic word recognition for handwritten historical documents. In: Proc. DIAL. (2004) 278–287
49. Chan, J., Ziftci, C., Forsyth, D.A.: Searching off-line arabic documents. In: Proc. CVPR. (2006) 1455–1462
50. Lemur search engine: http://www.lemurproject.org/.
51. Galago search engine: http://www.galagosearch.org/.
52. Zipf, G.: Human Behaviour and the Principle of Least Effort. Addison-Wesley, Cambridge, MA (1949)
53. Liu, T.Y., Yang, Y., Wan, H., Zeng, H.J., Chen, Z., Ma, W.Y.: Support vector machines classification with a very large-scale taxonomy. SIGKDD Explor. Newsl. **7** (2005) 36–43
54. Deng, J., Berg, A.C., Li, K., Fei-Fei, L.: What does classifying more than 10, 000 image categories tell us? In: ECCV (5). (2010) 71–84
55. Nister, D., Stewenius, H.: Scalable recognition with a vocabulary tree. In: Proc. CVPR. (2006) 2161–2168
56. Indyk, P., Motwani, R.: Approximate nearest neighbors: towards removing the curse of dimensionality. In: Proc. STOC. (1998) 604–613
57. Muja, M., Lowe, D.G.: Fast approximate nearest neighbors with automatic algorithm configuration. In: Proc. VISAPP. (2009) 331–340
58. Andoni, A., Datar, M., Immorlica, N., Indyk, P., Mirrokni, V.: Locality-sensitive hashing scheme based on p-stable distributions. Nearest Neighbor Methods in Learning and Vision: Theory and Practice (2006)
59. Philbin, J., Chum, O., Isard, M., Sivic, J., Zisserman, A.: Lost in quantization: Improving particular object retrieval in large scale image databases. In: Proc. CVPR. (2008)
60. Rath, T.M., Manmatha, R.: Word image matching using dynamic time warping. In: Proc. CVPR. (2003) 521–527
61. Balasubramanian, A., Meshesha, M., Jawahar, C.V.: Retrieval from document image collections. In: Proc. DAS. (2006) 1–12
62. Lowe, D.G.: Distinctive image features from scale-invariant keypoints. IJCV **60**(2) (2004) 91–110
63. Dalal, N., Triggs, B.: Histograms of oriented gradients for human detection. In: Proc. CVPR. (2005) 886–893
64. Bosch, A., Zisserman, A., Munoz, X.: Scene classification using a hybrid generative/discriminative approach. IEEE PAMI **30**(4) (2008) 712–727
65. C.L.A. Clarke, N. Craswell, I. Soboroff, Overview of the TREC 2009 Web Track (online resource).
66. Rath, T., Manmatha, R.: Features for word matching in historical manuscripts. In: Proc. ICDAR. (2003) 218–222