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# Connected Component Based Word Spotting on Persian Handwritten image documents

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**Abstract**

Word spotting is to make searchable unindexed image documents by locating word/words in a document image, given a query word. This problem is challenging, mainly due to the large number of word classes with very small inter-class and substantial intra-class distances. In this paper, a segmentation-based word spotting method is presented for multi-writer Persian handwritten documents using attribute-based classification and label-embedding. For this purpose, a hierarchical framework is proposed, in which at first, the candidate are selected based on connected components(CCs) sequence. Then, the query word is segmented to constructor CCs, and similar CCs count in the candidate region of document are selected based on their distances to the CCs count of the query word. As a result, the candidate regions are extracted. In the final phase, the query word is located only in the candidate regions of the document. A well known Persian handwritten text dataset, namely FTH, is chosen as a benchmark for the presented method. The results shows that the proposed method outperforms the state-of-the-art methods, 81.02 percent for unseen word class retrieval.

*Keywords:* Persian handwritten documents, connected component, attribute-based classification, label embedding.
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## 1. Introduction

Nowadays, printed or handwritten documents are stored digitally owing the advances in science and technology. The vast majority of these documents is confronted by the absence of transcription

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and annotation, and also, manual indexing is infeasible. Furthermore, presented optical character recognition (OCR) systems are not working properly on handwritten and old printed documents. Regarding the importance of looking up words in the documents for librarians and researchers, an alternative approach, named word spotting, is introduced to fulfil these requirements. The aim of word spotting, also called word searching and word image retrieval, is to locate the instances of the given query words in unindexed image document databases. Additionally, word spotting which is also considered as a content-based image retrieval (CBIR) strategy, is one of the most prominent methods for automatic document indexing. Various categorizations of word spotting techniques are presented in the literature of image document analysis. The most important one is based on the search spaces, in which two main categories exist: Segmentation-based approaches and Segmentation-free approaches. Segmentation-based approaches leverage an effective word segmentation method which is applied as a preprocessing step; afterwards, the query words are compared to the segmented words directly. The most important disadvantage of such approaches is their high rates of word segmentation error, especially for languages written in cursive scripts such as Persian, Arabic and Urdu. On the other hand, segmentation-free approaches do not require word segmentation. They locate the regions in the document which are the most similar to the input query word.

Another assortment is based on the query formats: query by example (QBE), and query by string (QBS). In QBE methods, the query is a word image, cropped once by the user in the document manually. Such approaches are commonly learning-free, and based on template matching techniques[1]. Since the user must select an instance of the query word in the document manually, QBE methods are inflexible against major writing variations of the words. In QBS methods, also called word retrieval in some studies [2, 3], the query is typed by the user and spotted in the image document. QBS has a distinguishing advantage over QBE, since preparing a query in plain text is much easier than an image instance. However, QBS requires annotated data for training which is not required in QBE. Segmentation-based QBE methods are mostly proposed in older approaches for word spotting, [4-6].

Some types of variable length features and dynamic time wrapping (DTW) techniques are prevalent in word spotting [7-11]. The DTW-based methods are very time consuming and only suitable for single-writer documents. These methods are only able to search observed closed words in the training set, and cannot handle the out-of -vocabulary (OOV) problem. Therefore, statistical model based approaches are applied to Latin [12] and Arabic [13] documents, which only need one instance of each letter in the document to train generalized hidden Markov models (gHMMs). Having used such models for cursive handwritten style, an effective letter segmentation method is also required. These approaches often work well on single-writer documents. Among other approaches of this category are methods based on shape matching [14-19]. In [20], synthetic data, user feedback, and some efficient features are used to improve word spotting results in printed historical documents. In [21], a multilingual word spotting scheme, using shape-based features of words, including: gradient, structural and concavity (GSC), and normalized correlation similarity measure, is presented. In [22], a measure of similarity between sequences which maps to a semi-continues HMM (SC-HMM) is applied as a word spotting system. The first word spotting system in printed Persian documents is proposed based on XNOR search, and a font recognition system to modify the font of input query as a preprocessing step [23].

Some researchers have different points of view to solve the problem of word spotting, as follows. In [24], word spotting is addressed as a HMM word verification problem. In this approach, a novel score normalization, i.e. conventional HMM filler model, is proposed. The efficiency of scale-invariant feature transform (SIFT), when DTW and HMM are applied, is empirically proven in [24-26]. Also, SIFT descriptor, where extracted over the corner points, and the Fisher kernel are investigated in [27] and [28], respectively. The pseudo-structural descriptor, as an approach based on Loci feature stored in a Hash structure, has been introduced in [29]. Recently, a word spotting scheme for printed documents is presented based on QBS segmentation in [3]. This scheme synthesizes string queries to word images, and then, the QBE technique is applied. In [30], a learning-based word spotting system is proposed for Arabic handwritten documents. In this system, the language model and the part-of-word (PAW) segmentation is hired to escape the word segmentation problems. In [31], a QBS word spotting system, based on contextual models is proposed for Chinese documents, in which a combination of a character classifier, and the linguistic and geometric contexts, is applied.

In some studies, document segmentation is carried out in the line level and the word spotting technique is applied to the segmented lines. In [32], the score of a text line is obtained using character HMMs, and the extracted line can be further spotted by arbitrary keywords. The modified token passing algorithm and recurrent neural networks, together with a bidirectional long short term memory (BLSTM), are applied in another line-based word spotting system [33]. A new sequence matching algorithm, named flexible sequence matching (FSM) , is recently introduced and applied for word spotting at the line level [34]. There are also several other predominant word spotting methods as follows. In [35], a segmentation-free QBE-based method is designed for historical documents which leverages gradient orientation around a high magnitude zone as a feature. In this work, a cohesive elastic matching, which only matches the informative parts of the words, is carried out to locate the query word. In [2], the approach of [35] is modified to adapt with the other type of query, i.e. QBS. In [36], a word spotting method for printed documents using block based image descriptors is presented. This approach hires descriptors in a template matching process, which satisfies some affine transformations. A system based on connected components (CCs), Euclidean distance transforms, and mapping constraint dynamic time wrapping is proposed in [37]. In this approach, a content-level classifier, based on strokes prior information, is used as a preprocessing step to enhance the input documents. In [38], a patch-based framework is proposed, where patches are presented by the bag of visual word (BOVW) models for SIFT descriptors, and latent semantic indexing is applied to feature vectors as a refinement step. Recently, a technique based on HOG descriptors for a fixed sized grid and sliding windows is proposed [39]. This approach employs an exemplar support vector machine (SVM) and product quantization to yield an enhanced and compressed representation. In [40], an approach is presented for word spotting in early printed documents, in which the characters are indexed using self-organizing map-based (SOM-based) clustering. In this work, a matching process is carried out using the modified dynamic time wrapping, based on SOM similarities and characters information. In [41], both bag-of-feature and HMM techniques are combined in a patch-based framework to buildup a segmentation free word spotting scheme.

Some of the recent learning-based methods, comply with both types of queries, i.e. QBE and QBS. In a segmentation based word spotting system, proposed in [19], the words are represented by a sequence of S-characters , a sub-pattern which is presented by a profile based feature vector. Other outstanding methods of this type include the attribute-based approaches of [42], and [43], which represent both image and text words in low dimensional fixed length vectors. In these approaches, the unified representation of words image and text string, along with common subspace regression allow to search by both query formats; there is no need to synthesize the string query to an image. In [44], a deep convolutional neural network, called PHOCNet, is introduced which enhances the previous work by incorporating pyramidal histogram of characters (PHOC) to represent image/text words. Some recent researches have also used this representation and its modified versions for word spotting and recognition tasks [45,49-52].

The main challenges of word spotting owes to writing style variations in multi-writer documents and out-of-vocabulary (OOV) spotting in lexicon-based methods. To tackle this problem, in this paper a multi-writer lexicon-based segmentation-based scheme for Persian handwritten word spotting

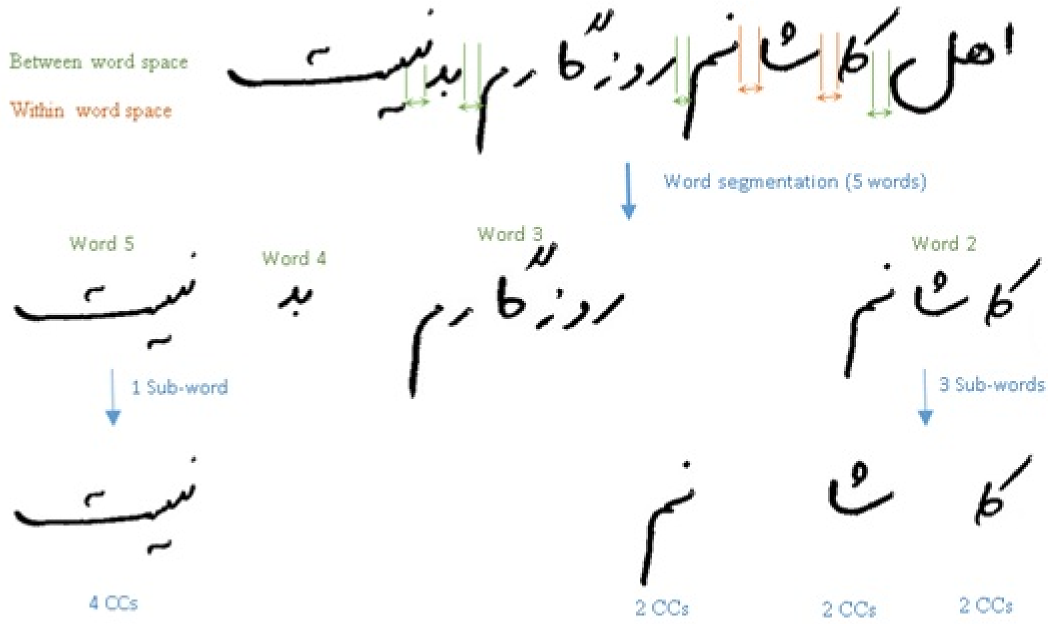


Figure 1: A sample of Persian script with details: The between and within word space, words, sub-words and connected components (CCs).

is proposed. It can perform OOV spotting and accept both types of queries, i.e. QBE and QBS. This work follows our previous work introduced in [42, 43, 45].

## 2. Persian script characteristics

Persian writing, also known as Parsi and Farsi, is the official language in Iran, Tajikistan and Afghanistan which always cursive even when printed, and written horizontally from right to left. Similar to Arabic, each character can have four different shapes according to their location in the word and previous character (first, middle, end and isolated).

Each Persian word consists of a number of sub-words, in some literature named Part of Word (PAW), which is composed of a number of Connected Components (CCs). In addition, some of Persian characters contain a unique main body (overall shape) and the differences are number and position of special symbol such as dots and zigzag bars, therefore the main body of Persian character set is 18 shapes. Based on main body grouping, 116 different shapes of Persian character have had 58 main body category. Therefore, each connected component is a sequence of connected main bodies, dot or zigzag bars. In the other words, CCs in Persian writing style can be divided into two main categories. Major connected components which include main body of character which lie on baseline and includes main body of isolated character or several connected characters. Minor connected components includes dot or zigzag bars which have small size and locate in up/down of baseline. Most of the time in handwritten documents, dots in multi-dot characters stick together and make a unit connected component.

In Persian writing style, two type of white space is existed: first, like most languages, there are space between words, second, white space between sub-words exists (within word space)(figure 1). These properties makes it more challenging than other languages in document image analysis task, especially handwritten style.

## 3. A brief review on Attribute based word spotting based on label embedding

The presented work is based on state-of-the-art model which provide a new effective and efficient word representation to segmented-based word spotting and recognition [43, 49, 50]. Therefore, the mentioned method is briefly described.

In word spotting and recognition, attributes is used to learn discriminative representation by sharing information between words. Selection of attributes is a task-dependent process and in this work, word discriminative and appearance independent attributes must be defined. In [43, 50] Pyramid Histogram of Characters (PHOC) is used as labels of attributes. For feature extraction, word images are divided to K region (2 rows and 6 columns) and SIFT descriptor are extracted from each region of word images. Then, the extracted descriptors are enriched by appending normalized horizontal and vertical coordinates where normalized between -0.5 and 0.5. The enriched representation is used to learn an independent GMM vocabulary on each region. These GMMs are merged and renormalized to 1. The Fisher Vector (FV) and SVM as state-of-the-art encoding and classification method is used to transform input word image to attribute scores. In training phase, PHOC attributes and extracted feature vector is used to learned attribute model based on SVM classifier. Since the attribute score of images are not in the range of binary PHOCs, calibration of PHOCs and attribute scores is needed. Platt scaling, Canonical Correlation Analysis (CCA) and Kernelized Canonical Correlation Analysis (KCCA) as calibration method is used.

In the resulting common subspace, text labels and images of the same word is close together, since QBE and QBS can be done simultaneously in this framework. Due to the use of attributes, words which has not been seen in training phase (OOV), can be retrieved. Also word spotting and recognition problem convert to a simple nearest neighbour problem.

## 4. proposed method

In this paper a segmentation-based word spotting system for Persian multi-writer documents is proposed. A two phases system are introduced which first phase determines the candidate region by connected component based windowing. The next level only select candidate region With the number of connected components close to the input query word and rank the candidates based on attribute-based method which is introduced in [43] and extended version for Persian handwritten in [45]. In [43], a new paradigm to embed word images and word labels in a common Euclidean space for segmentation-based word spotting and recognition is proposed which change nature of this problems to simple nearest neighbour problem. This common subspace is learned by support vector machine (SVM) which label and image of the same word enforced to be close. The paradigm have several advantages: both type of query (QBE and QBS) can be applied in a unique framework. Out-of-Vocabulary (OOV) spotting and recognition is possible using a limited set of training data (lexicon). The state-of-the-art image descriptor can be used.

The pyramid histogram of characters (PHOC) as a text label embedding method, represent distribution of positional character in a word in a binary mode. Binary flags shows the presence of a character in approximate location in the word using a hierarchical approach. Figure 3 shows the PHOC representation by standard Persian characters of SHAHROOD. In level 2, existence of 50 frequent bigram in first and second half of word are added to final PHOC which encode adjacent characters relation.

The characteristic of Persian style is considered for text label embedding in our previous work[45-47] which named pyramid histogram of Persian signs (PHOPS) and each vector has 64 dimension include 56 main body of Persian characters in addition to 8 cases of dots and zigzag bars. The most important advantage of the presented text label embedding is the ability of Persian connected

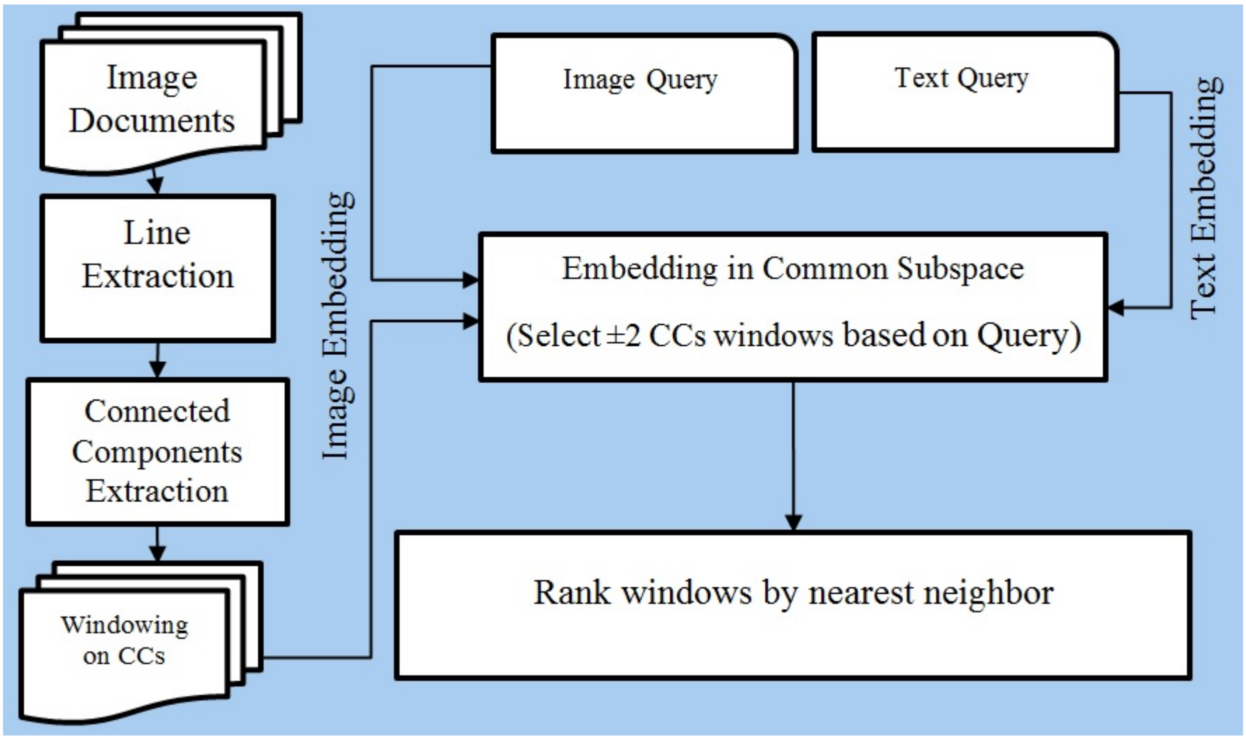


Figure 2: An overview of proposed method

component spotting along with word spotting. The proposed method in this paper applied embedding method to make a word spotting system. In the following, connected component spotting system to select candidate region is explained.

for all documents in dataset, connected component of each lines is exclusively extracted. An adaptive block-based text line segmentation algorithm is used to extract document's lines[48]. Depending on the structure of Persian words, sequences of two to seven adjacent components from right to left is windowed. This window is overlapped, so that the difference of two consecutive windows is only in one connected component (figure 3). All extracted window is embeded to common subspace as a word image, and then index by position of window and attribute vector.

entrance query, text(QBS) or image(QBE),is embeded to common subspace and is counted its connected components. candidate window with two CCs fewer than query to two CCs more than query are embeded to common subspace. candidate window is ranked based on Euclidean distance with query.

## 5. Experiment results and discussion

### *5.1. datasets*

To show the abilities of proposed system in OOV spotting and robustness to handwritten variation, two different datasets in train and test phase is used. For training phase, FARSA dataset [51] is used which is contained 30000 isolated word in 300 class of common formal words in Persian language.some sample of FARSA dataset is shown in figure 5. In test phase, 100 different documents of FHT dataset[52] is used, which contain 10000 document where wrote by 250 writer in different education level and ages. three sample of FHT dataset is shown in figure 6.


Figure 3: PHOC representation of SHAHROOD in three levels by Persian character set. All of partial histograms in all levels are concatenated to make final PHOC histogram.

Figure 4: a sample of line with exteracted connected components and sample windows with 2 to 5 connected components.

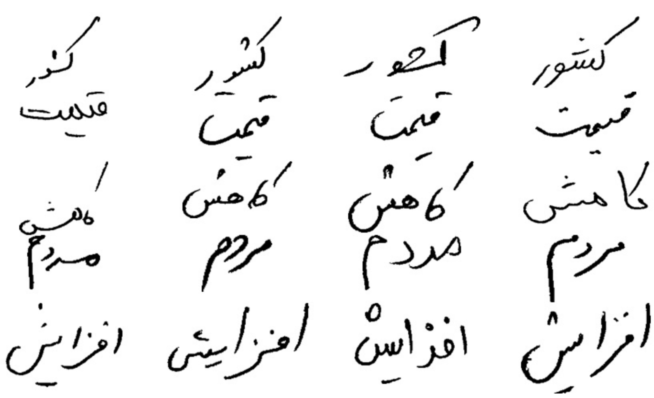

Figure 5: Some samples of FARSA dataset

Figure 6: three samples of FHT dataset

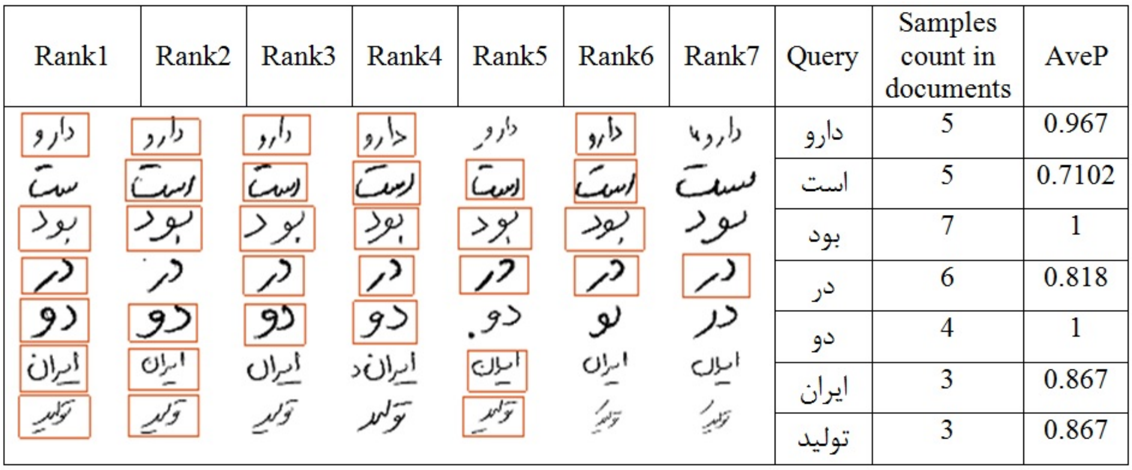


Figure 7: sample of MAP for some query

Table 1: Result

| Method | CCA | KCCA |
|---|---|---|
| QBE | 77.72 | 78.14 |
| QBS | 80.41 | 81.02 |

*5.2. evaluation*

For evaluate content-based image retrieval system, such as word spotting system, mean average precision (Map) is used. Map calculate mean of average precision (AP) for each query. sample of AP calculation is shown in figure 7. Equatuin of MAP is:

$$AP = \frac{\sum_{i=1}^{W} \frac{i}{Rank_i}}{W} \tag{5.1}$$

Where W is number of relevant word location in document for that query and i/Ranki=0 if word I is not retrieved. Calculate the mean of average precisions (APs) for all queries to gain Map. The Map for proposed word spotting system by CCA and KCCA is shown in table 1.

## 6. conclusion

In this paper a segmentation based word spotting method is proposed for Persian handwritten documents. candidate region selection proccess based on connected components windowing decrease the number of windows that must be processed, dramatically.Because of using Attribute based classification and label embedding techniques to represent text and image in a common subspace, OOV spotting with high accuracy is done.

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