



Keyword Spotting in Historical Handwritten Devanagari Documents: A Graph Based Approach

Sharada B.¹, Sushma S. N.*²

^{1, 2}Department of Studies in Computer Science, University of Mysore,
Manasagangotri, Karnataka, INDIA

Abstract: Massive quantities of historical documents are available in National libraries that are still not digitized. This information would go exhausted if not preserved in digital form. The problem of information retrieval from handwritten Indian scripts is challenging task due to its huge changeability in writing styles and its large vocabulary. Keyword spotting is a substitute system used instead of recognition systems. Keyword spotting in handwritten documents is an important and difficult job for the document image analysis researchers. It has various applications that include conserving the world's cultural heritage, accessing handwritten books through the Internet and reading postal address. Even though the research in handwritten document image analysis is vigorous and widespread, it is very difficult to attain high accuracy. Most of the keyword spotting approach available is based on statistical representation of word image with less works for Indic scripts. This paper presents an effective approach for keyword spotting from historical Devanagari handwritten documents using graph based method where the structural properties of the word images are modeled. Experimentation is conducted on historical handwritten Shankaracharya's documents written in Devanagari script. The results are promising in terms of accuracy and efficiency. The authors have also examined our approach for standard database of Bangla and Gurumukhi scripts and the consequent results are reported.

Keywords: Keyword Spotting; Segmentation; Graph Extraction; Ranking; Mutual Word Matching; Graph Edit Distance

I. Introduction

In order to preserve world's cultural heritage, many national libraries have started massive digitization of valuable historical handwritten documents. Many digitization initiatives exist worldwide to convert historical documents to digital libraries. George Washington's papers at the Library of Congress and Isaac Newton's papers at the University of Cambridge Library [1, 2] are the some examples for valuable handwritten historical documents. Due to huge diversity of handwritten fashions, handwritten keyword spotting has long been a dynamic research area. The purpose of keyword spotting is for mining of the useful information that these manuscripts contain by generation of digital libraries. Keyword spotting system is used to overcome the shortcoming of recognition methods. The digitization process and the use of standard formats to store the images in digital libraries guarantee the enduring preservation of the documents. Recent advances in imaging, storing, and network technology have paved the way for initiating several schemes designed for digitization of historical books and manuscripts. However, the spotting the word of unconstrained handwriting is still a challenging task due to the divergent writing styles. In 2003, an effort was made by Cha et al [3] for insufficient handwriting recognition performance leads to low performance of text search. OCR will work accurately for printed documents, but not for handwritten documents. In content-based image retrieval (CBIR), Keyword detection of document image is a standard problem exemplar. Keyword spotting retrieves all instances of a given query keyword from a document in any language. Major applications of keyword spotting include handwritten notes, digital libraries and historical document retrieval, which involve large volumes of documents and entail efficient techniques of document information retrieval. The first application of keyword spotting to handwritten text was presented a little later by for ancient books for medieval handwritten text in Latin and Semitic alphabets by Konidaris et al [4]. A large amount of explorations have been done in the area of recognition of handwritten digits, characters and word spotting in English, Chinese and Latin, but it is very difficult to spot words in offline handwritten Devanagari scripts. The query word is searched in the documents and relevant words are retrieved and ranked, where the ranking criterion is a similarity score between the query and the candidate words is computed by Mondal et al [5]. Keyword

spotting approaches can be query-by-string and the query-by-example, depending on how the input is specified. In query-by-string approaches, character models are trained in advance and at query time the models of the characters forming the string are concatenated into a word model and the probability of each word image is evaluated. Once trained, these approaches allow searching for any possible keyword. In query-by-example approaches, the input is an image of the word, and the output is a set of word images that are most similar in appearance to the query image. This can be seen as content based image retrieval (CBIR) task. The result is based on a distance measure between the query and all candidate word images, hence no training is involved. Generally, high-level features and low-level features of handwriting analysis are used in keyword spotting. High-level features are more abstract and systemic features, such as ascenders, descenders and loops, which are typically more concerned with the object as a whole, or larger components of it. These features do not work very well on unconstrained handwriting, because the results of high-level feature extraction tend to be erroneous due to the large shape variations in the natural cursive handwriting.

On the other hand, low level features are concentrated more on individual components that provide details rather than the overview. The features such as entropy, profiles, Zernike moments, point features are low-level. They are usually less informative but more reliable [6, 7, 8, 9]. Statistical methods are done in majority of works reported on handwritten Devanagari documents. For handwritten devanagari word images, we propose a structural representation. Historical handwritten Devanagari document sources of the Oriental Research Institute [ORI] @ Mysuru is used for testing and validation of different stages. In the paper, Section 2 presents a brief related works of Keyword spotting. Section 3 gives a detailed explanation about the proposed methodology. Section 4 presents the experimental results which are followed by conclusions and future work in Section 5.

II. Related Works

Originally, word-spotting was formulated for detecting words or phrases in speech messages (Adamek et al. 2003), and the next ended to locate words in typed text documents (Fischer et al. 2012). In (Lavrenko et al. 2004) it was first proposed for offline handwritten documents, as a way to automatically index historical document collections. This enabled the paradigm of search engines for handwritten document images (Leydier et al. 2009). The word spotting idea for handwritten manuscripts was initially proposed in (Rath et al. 2007). The literature of keyword spotting can be classified into two main approaches: segmentation based and segmentation free, depending upon whether the document image is segmented or not. Segmentation based approach involves three levels of page segmentation like segmenting page into lines, words and characters. Some of the drawbacks of detection of words using segmentation techniques are partial occlusion and over or under segmentation. In Segmentation free approach, the document image is considered as a whole and does not need any segmentation. It uses the concept of sliding window for spotting of words (Rusinol et al. 2011, Almazan et al. 2014).

Many statistical as well as structural features such as column features, pixel count features, gaussian filter features, local gradient histogram, sliding window, binary gradient structural and convexity (GSC), discrete cosine transformation profile, ink transition, chain code (CC), zoning, Fourier coefficients, SIFT features, projection profiles, upper/lower word profiles and so on [3, 9, 4, 5] are used for representation of word images. Besides, set of features were explored and combined in order to improve the word image representation. For estimating similarity between query and candidate word image, various distance measures were used such as HMM and DTW [10, 11, 12, 13]. For word spotting using character shape coding, the word images are further segmented into smaller units and corresponding set of predefined codes are generated which is sensitive to error in segmentation of character. This method is called analytical approach which involves segmentation of word images into characters. In word shape coding, the whole word image is used for matching by Adamek et al [14]. Gradient angles are selected as local features and cohesive elastic distance is used for matching of word images [15, 16]. This is called holistic approach which involves image-by-image matching technique. In 2015 Mondal et al [5], line based segmentation method is used which works on the basis of DTW. BLSTM Neural Networks and CTC Token Passing algorithm have also been used for spotting words with elevated retrieval result [8, 12, 17]. Query-by-string approaches are like OCR-based handwriting recognition systems which usually require training process followed by testing, whereas in query-by-example approaches, based on the similarity measure a list of ranked word images are generated which doesn't require any training. For the word images unique features like Profile features, ink transition profiles, binary gradient, structural and convexity features, upper/lower word profiles, and discrete cosine transformation are used for representing word images. Besides, multiple features were explored and combined in order to improve the word image representation [compound features scheme]. For calculating similarity between word images, various distance measures were used. In segmentation-free approach, for compressed version of each document image, codebook of shapes created and sliding window technique is used for spotting the words in documents which is known as Document-based word spotting.

Nowadays, capturing and modelling the structural properties of objects using Graph based representation has become a trendy approach in pattern recognition domain. However, the employment of graph representation in the handwritten word spotting application is still very rare. There are only a few attempts made in handwritten recognition research with graph representation or relative concepts up to now. From the literature survey, the

authors understand that the methods proposed are used to detect the words of different languages. Among all these languages work on Devanagari word is not so common to that of English and Chinese words [15, 6]. Many graph based approaches are found in the literature for matching the word images of different languages like English, Chinese, Latin. Structural representation is not applied for spotting the handwritten Devanagari words. However the authors feel that using graph theory, the words would be detected easily and would naturally make some space in the field of word spotting. This motivated us to make an attempt to develop a keyword spotting system for handwritten devanagari documents based of structural representation. Devanagari is the basic script of many languages in India, such as Hindi, Sanskrit, Nepali and Marathi. Devanagari is half syllabic in nature. Devanagari script contains 13 vowels and 36 consonants. Devanagari word has three zones such as lower, middle and upper zone. The upper zone contains the modifiers, and lower zone contains lower modifiers. The upper zone and middle zone are always separated by the header line called Shirorekha [18, 19, 20, 21]. As Hindi is the Indian national language, Devanagari has got the position of national vernacular.

III. The Proposed Method

In the proposed method, a given query handwritten word image is matched with all the handwritten word images in the source documents and similar words are spotted in the documents. A handwritten document is scanned and stored in word image database. A group of operations are performed such as preprocessing, segmentation of document images [into candidate word images], graph representation of word images and graph extraction using Nearest Neighbourhood Analysis [NNA]. The given query image and candidate word images are compared by mutual word matching using Graph Edit Distance [GED], corresponding similarity matching score is calculated. Based on this similarity matching score, similar keywords images in handwritten documents are spotted.

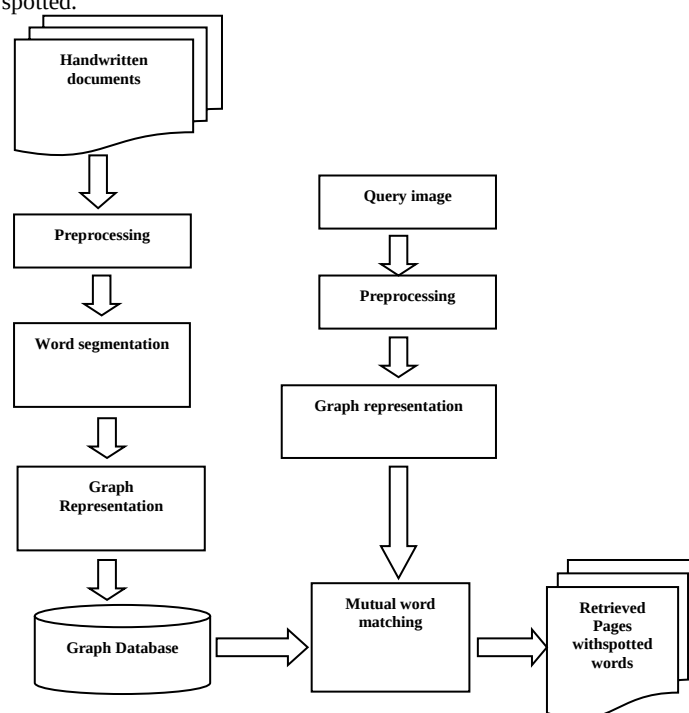


Fig. 1. Keyword spotting system overview

A. Preprocessing and Segmentation

Pre-processing processes are vital in order to progress the quality of input document images as the handwritten historical documents are characterized by low image quality and huge quantity of noise. In order to eradicate the noise in the image, Gaussian filtering is used and then the image is converted into a binarized image. Based on some threshold value attained through Otsu's method [22] skew angle correction is achieved using horizontal projection profile, which can be performed for different angles and the largest magnitude variations correspond to the skew angle. The width of a line like object with many pixels is reduced to just single pixel using skeletonization process. To remove all types of variations during the writing, normalization is performed and standardized data is obtained. The preprocessed image is given as input to the segmentation process. Segmentation is performed using projection profile method. In this stage the binary image is separated into lines and words. In line segmentation, the text lines are detected by finding the valleys of the projection profile computed by a row-wise sum of black pixels. This horizontal projection profile shows large values for the headline of the individual text line. The border line between two text lines is indicated by the position among two successive headlines, where the projection profile elevation is minimum. Vertical projection profiles are used for word segmentation from the text line image [6].

The zero valley peaks in the profile represents the word space. From first stage, segmented line is generated and is given as input for second stage to perform word segmentation where the line segmented into words.

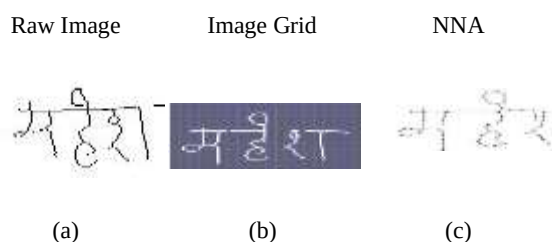


Fig. 2. Sample results of NNA

B. Graph Representation

In pattern recognition there are two object modelling approaches: statistical and structural. The patterns in statistical approach are represented using set of features [feature vectors] and patterns in structural approach are represented using graphs. A graph representation is a structural representation in which the relation (edges) between different objects (nodes) are illustrated. In “Structural representation” for handwritten Devanagari words, each word is represented as a graph G . Let LV and LE be a finite label sets for nodes and edges, respectively. A Graph G is a four tuple (V, E, μ, ν) , where, V is set of vertices or nodes.

$E \subseteq V \times V$ represents set of edges

$\mu: V \rightarrow LV$ is the vertex labelling function, and

$\nu: E \rightarrow LE$ is the edge labelling function.

The number of nodes of a graph G is denoted by $|G|$ called the order of graph G , while G symbolizes the set of all graphs over the label alphabets LV and LE [23]. For graph representation, the given handwritten document image is normalized and segmented word images are partitioned into predetermined grid known as segments of equal size. For each segment, center of mass is computed. This center of mass performs as a node for each segment and neighbor nodes are determined for each node. According to the NNA insertion algorithm, the undirected edges (u, v) are inserted into the graph. The NNA algorithm analyses the four neighboring segments on top, left, right, bottom of a node $u \in V$. If neighboring segments of u is represented by a node $v \in V$ an undirected edge (u, v) between u and v is inserted into the graph. This center of mass acts as a node for each segment. Center of mass is not determined if foreground pixel is not present in the segment and hence node cannot be constructed for this segment. The neighbor nodes of each node are determined. The dimension of the grid is represented by number of rows r and number of columns c and is calculated using:

$$r = \frac{\text{height of } T}{h} \quad \text{and} \quad c = \frac{\text{width of } T}{w} \quad (1)$$

where, T is the thinned image of the original word image, h and w denote the user defined height and width of the resulting segments. Now the word image T is divided into $r \times c$ equal sized segments.

Where for every fragment s_{ij} , ($i = 1, \dots, r$; $j = 1, \dots, c$), centre of mass (x_m, y_m) is calculated using:

$$x_m = \frac{1}{n} \sum_{w=1}^n x_w \quad \text{and} \quad y_m = \frac{1}{n} \sum_{w=1}^n y_w \quad (2)$$

Where, n is the number of foreground pixel of segment s_{ij} , x_w and y_w denote the x - and y -coordinates of the foreground pixels in s_{ij} . For the centre of mass (x_m, y_m) , a node is inserted into the resulting graph and labeled by the (x, y) -coordinates. Node is not inserted for the segment which does not have any foreground pixel [no centre of mass]. Undirected edges (u, v) are inserted into the graph according to Nearest Neighbourhood Analysis (NNA) which is a edge insertion procedure algorithm. The nearest neighborhood procedure analyses the four neighboring segments on top, left, right, bottom of a node $u \in V$. If neighboring segments of u is represented by a node $v \in V$ an undirected edge (u, v) is inserted into the graph between u and v .

C. Graph Edit Distance (GED)

Graphs can be categorized as directed and undirected graphs, where two nodes are joined by directed or undirected edges respectively. Graph matching can be achieved using either inexact or exact matching methods. For handwritten word matching, an Inexact graph matching method are used where two non-identical graphs are compared. An error-tolerant Inexact graph matching technique called Graph Edit Distance (GED) is used which is most powerful and flexible approach existing [24]. Using Graph Edit Distance (GED), the dissimilarity between the query word graph and all the candidate word graphs are calculated. Finding the dissimilarity of two graphs by the using minimum amount of distortion necessary to transform one graph into other graph is the main idea of the graph edit distance. The distortion model is comprises of six types of edit operations: insertion, deletion and substitution for both nodes and edges. An edit path from g_1 to g_2 is the sequence of edit operations $(e_1, \dots, e_k)$ that transforms g_1 into g_2 . There are several edit paths available to transform g_1 to g_2 . So the cost for each edit

operation is associated and the least cost edit path to transform g_1 into g_2 is the GED. $g_1(V_1, E_1, \mu_1, v_1)$ and $g_2(V_2, E_2, \mu_2, v_2)$ are query and candidate graphs respectively.

Graph edit distance between two graphs is calculated using:

$$ged(g_1, g_2) = \min_{(e_1, \dots, e_k) \in \gamma(g_1, g_2)} \sum_{i=1}^k c(e_i) \quad (3)$$

Where, $\gamma(g_1, g_2)$ represents the set all of edit paths to transform g_1 to g_2 , $c(e_i)$ represents the cost of the edit operation e_i .

D. Mutual word Image Matching

Mutual matching is performed based on matching between query graph g_q with the set of all word graphs $G = \{g_1, g_2, \dots, g_n\}$ in word image database. A sub-optimal algorithm known as Bipartite Graph Matching [24] is used for mutual matching. A rank list is computed between query graph g_q with the set of word graphs in database as the matching score. Ranking between g_i and g_q is calculated using:

$$rank(g_i) = 1 - \frac{d(g_i, g_q)}{\max[d(g_i, g_q)]} \quad (4)$$

Where $d(g_i, g_q)$ indicates graph edit distance between g_i and g_q , $\max[d(g_i, g_q)]$ indicates maximum cost edit distance between g_i and g_q . Using this, the ranking list is normalized between 0 to 1, the ranking score is sorted and corresponding words are highlighted in handwritten documents.

IV. Experimental Results

As per our knowledge, this is the first effort of using structural representation in keyword spotting of handwritten devanagari documents. At present as there is no standard dataset available for handwritten devanagari document images, for our experiments we used three datasets of devanagari documents. A handwritten historical devanagari document collected from ORI @ Mysuru which contains scanned handwritten historical devanagari document images which contains 19 pages of Shankaracharya's manuscripts, second database contains scanned handwritten devanagari document with 23 handwritten document images collected from individuals of different professions and third database consists handwritten documents which is collected from 15 diverse writers which is used by Garg et al [25]. The results of the keyword spotting using structural representation and statistical representation are compared. In statistical representation, keypoints of word image are used for representation i.e., features like end-points, branch-points and number of connected components of word image are used as features. The similarity between query word and all candidate word images are computed based on the mutual word matching criteria and ranked accordingly. For the query word image, the top ranked candidate word images are regarded as similar word images and are spotted in document image. The results of keyword spotting of handwritten devanagari documents using graph based approach is shown in Figure 3

Precision (PR), Recall (RC) and F-Measure (FM) are computed to determine the performance of keyword spotting. For the assessment of the proposed approach, 6 different query word images and its frequency of occurrences in the source document image is noted. The ground truth of these words is shown in Table 1. Let W_f be the total number of keyword instances and W_{cs} is the correctly spotted keyword instances [23]. Then,

$$Precision = \frac{W_{cs}}{W_f} \times 100 \quad (5)$$

$$Recall = \frac{W_{cs}}{W_d} \times 100 \quad (6)$$

$$F - Measure = \frac{W_{cs} \times 2(RC \times PR)}{W_f \times (RC + PR)} \quad (7)$$

Where, precision indicates the percentage of the spotted words that exactly matches the query word. Recall indicates the percentage of the words same as query word that are successfully retrieved from the word database. The keyword spotting performance of both structural and statistical approach in terms of recall and precision as well as F-measure for devanagari documents is shown in Table 1. We can see that in both approaches, the proposed structural approach outperforms the statistical approach. Keyword spotting using graph based representation gives better results. The precision and recall are represented as chart in Fig.4 and Fig.5.

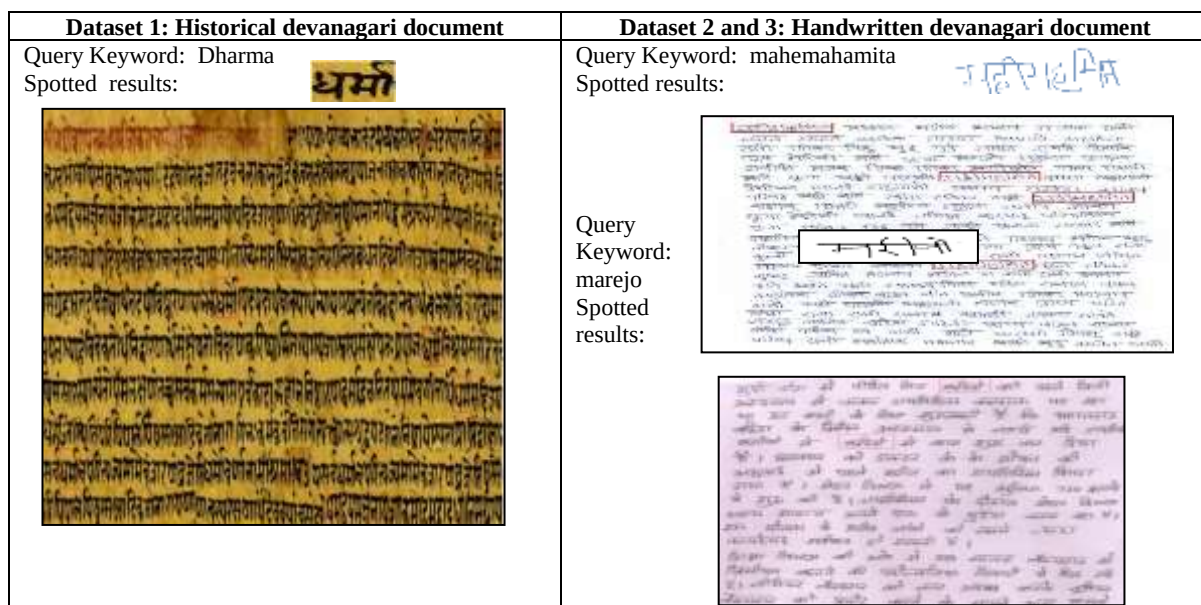


Fig 3. Qualitative Keyword spotting results for the query “dharma” from dataset 1 , query word “ mahemahamita” from dataset 2 and query word “ marejo” from dataset 3

Table 1. Performance of Keyword spotting system

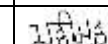
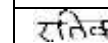
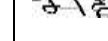
Sl No .	Document type	Docume nt size	Query Keyword image	Word occurrenc es in database	Precisio n	Recal l	F-measur e	Precisio n	Recal l	F-measur e
					Using Structural representation			Using Statistical representation		
1	Historicaldevanag ari document [Dataset 1]	19 pages		24	89.34	86.19	88.94	77.61	64.70	74.43
				19	85.76	89.67	86.94	76.16	76.66	82.86
				14	88.93	89.89	89.34	74.49	76.34	77.24
2	Handwritten Document [Dataset 2 and 3]	23 pages		27	87.54	89.93	87.62	79.16	70.83	76.66
				16	87.71	88.35	86.10	78.19	80.67	79.19
				11	89.23	88.93	89.93	74.49	79.29	77.25
Average					88.08	88.82	87.78	76.68	74.74	77.93

Fig.4. Precision and recall of keywords potting by statistical representation.

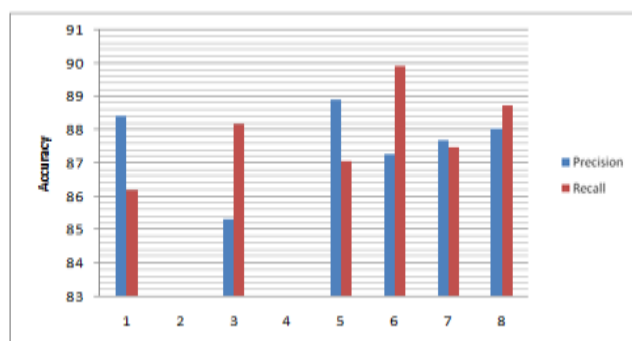
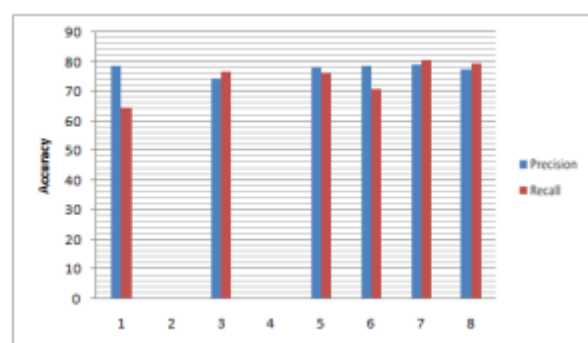


Fig.5. Precision and recall of keywords potting by structural representation



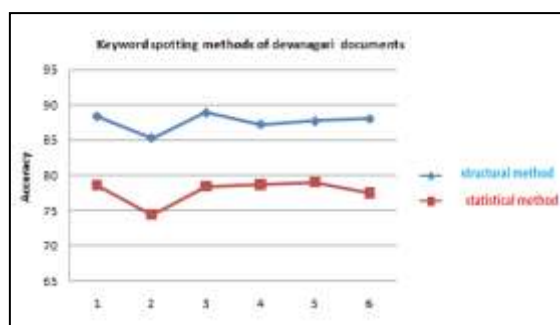


Fig.6. Comparison of performances of different keyword spotting of devanagari documents.

Methodology	MAP [Handwritten Devanagari document]
Proposed Graphbased keyword spotting	88.22
Statistical feature based keyword spotting	76.45

Table.3. Mean Average Precision results of different keyword spotting methods of handwritten Devanagari document

V. Conclusion and Future Work

In this paper, a graph based approach for spotting of historical handwritten Devanagari words is illustrated. The accuracy of proposed work directly depends on the handwriting styles. Although the majority of available word matching algorithms are based on statistical representations, challenge is now made in on structural representations. Statistical representation ignores the dependencies between observations, whereas a graph conserves these dependencies and relations. There are few works reported using structural representations for word spotting which is limited to languages such as English, Chinese, Latin and Arabic. However, the proposed work is the first attempt for spotting keywords from handwritten devanagari document images using graph representation.

In this paper, the authors have presented a robust and fast matching approach for word spotting in historical documents. The authors have shown the comparison of performance of different keyword spotting methods. Extensive experimentation conducted using the devanagari documents shows that systems based on structural representation significantly outperforms existing techniques. Significantly, it has been shown that for graph based representation on a handwritten devanagari document dataset, the average keyword spotting accuracy is 88.22%. Also the proposed method is tested for word spotting of Gurumukhi documents and the results are attractive. It can be concluded that the proposed approach efficiently performs keyword spotting in handwritten devanagari documents. Considering the enormous complexity of historical handwritten devanagari script, the contribution of the proposed approach may be considerable with satisfactory performances. The proposed approach is well suitable for keyword spotting of historical devanagari documents. It can be expanded for the spotting words in various south Indian languages. Also, segmentation free word spotting methods and adopting a complete indexing method can be the future research. The overall accuracy of the keyword spotting system depends on suitable image processing techniques used for historical document images.

References

- [1] T. M. Rath and R. Manmatha, "Word spotting for historical documents," in International Journal on Document Analysis and Recognition (IJ DAR), vol. 9 pp. 139–152, 2007.
- [2] R. Plamondon and S. Srihari, "Online and off-line handwriting recognition: A comprehensive survey," in IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 22, pp. 63–84, 2000.
- [3] T. Konidaris, B. Gatos, K. Ntzios, I. Pratikakis, S. Theodoridis, S.J. Perantonis, " Keyword guided word spotting in historical printed documents using synthetic data and user feedback," in International Journal of Document Analysis and Recognition, vol. 9, pp.167–177, 2007.
- [4] J. Almazan and A. Gordo and A. Fornes and E. Valveny, "Segmentation free Word Spotting with Exemplar SVMs," Pattern Recognition, 2014.
- [5] J. Almazan , A. Gordo , A. Fornes and E. Valveny, "Word Spotting and Recognition with Embedded Attributes," TPAMI, 2014.
- [6] S. Wshah, G. Kumar, V. Govindaraju, "Script independent word spotting in offline handwritten documents based on hidden markov models", Frontiers in Handwriting Recognition (ICFHR) 2012 International Conference on, pp. 14-19, 2012.
- [7] V. Frinken, A. Fischer, R. Manmatha, H. Bunke, "A Novel Word Spotting Method Based on Recurrent Neural Networks", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 34, no. 2, pp. 224, Feb. 2012.
- [8] I. B. Messaoud, H. Amiri, H. E. Abed, V. Margner, " Document Preprocessing System – Automatic Selection of Binarization," in IAPR International Workshop on Document Analysis Systems, 2012.
- [9] T. M. Rath and R. Manmatha, "Word image matching using dynamic time warping," in CVPR, vol. 2, pp.521, 2003.

- [10] A. Jose, R. Serrano and F. Perronnin, "Handwritten word-spotting using hidden Markov models and universal vocabularies," in *Pattern Recognition*, vol. 42, pp. 2106-2116, 2009.
- [11] S. Kim, S. Park, C. Jeong, J. Kim, H. Park, G. Lee " Keyword Spotting on Korean Document Images by Matching the Keyword Image, " in *Digital libraries*, vol. 3815, pp. 158-166, 2005.
- [12] C. L. Liu, J. Kim, J. H. Kim, "Model-based stroke extraction and matching for handwritten Chinese character recognition," in *Pattern Recognition* vol. 34, pp. 2339-2352, 2001.
- [13] T. Aducci and N. O. Connor, "Efficient contour-based shape representation and matching," in *ACM SIGMM International Workshop on Multimedia Information Retrieval*, 2003.
- [14] Y. Leydier, A. Ouji, F. L. Bourgeois and H. Emptoz, "Towards an omnilingual word retrieval system for ancient manuscripts," in *Pattern Recognition* vol. 42, pp. 2089-2105, 2009.
- [15] T. Novikova, O. Barinova, P. Kohli, Lempitsky, " Large-lexicon attribute consistent text recognition in natural images," *Computer Vision - ECCV*, 2012.
- [16] S. Mozaffari, K. Faez, V. Märgner and H. E. Abed, "Two-stage lexicon reduction for offline Arabic handwritten word recognition," in *International Journal of Pattern Recognition and Artificial Intelligence*, vol. 22, pp. 1323, 2008.
- [17] A. Andreev and N. Kirov, "Some variants of Hausdorff distance for word matching," in *Review of the National Center for Digitization*, vol. 12, pp. 3-8, 2008.
- [18] S. H. Cha, C. C. Tappert, S. N. Srihari, "Optimizing Binary Feature Vector Similarity Measure using Genetic Algorithm and Handwritten Character Recognition," in *International Conference on Document Analysis and Recognition*, vol. 02, pp. 662, 2003.
- [19] N. I. Cho and S. K. Mitra, "Warped discrete cosine transform and its application in image compression," in *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 10, pp. 1364-1373, 2000.
- [20] U. V. Marti and H. Bunke, "Using a statistical language model to improve the performance of an HMM-based cursive handwriting recognition system," in *Journal of Pattern Recognition and Art. Intelligence*, vol. 15, pp. 65-90, 2001.
- [21] K. A. Senthildevi and E. Chandra, "Keyword spotting system for Tamil isolated words using Multidimensional MFCC and DTW algorithm," in *International Conference on Communications and Signal Processing (ICCSP)*, 2015.
- [22] S. Abirami and D. Manjula, "Profile Based Information Retrieval from Printed Document Images," in *International Conference Computer Graphics, Imaging and Visualization*. Vol. 3, pp. 268-272, 2013.
- [23] A. Shrivastava, T. Malisiewicz, A. Gupta, and A. A. Efros, "Datadriven visual similarity for cross-domain image matching," in *ACM TOG*, vol. 30, pp. 154, 2011.
- [24] D. G. Lowe, "Distinctive image features from scale-invariant keypoints," in *International journal of computer vision*, vol. 60, pp. 91-110, 2004.
- [25] V. Frinken, A. Fischer, R. Manmatha, H. Bunke, "A novel word spotting method based on recurrent neural networks," in *IEEE Trans. Pattern Anal. Mach. Intell.* Vol. 34, pp. 211-224, 2012.
- [26] V. Lavrenko, T. Rath, R. Manmatha, "Holistic Word Recognition for Handwritten Historical Documents," in *Proc. Doc. Image Anal. Libr. DIAL'04*, pp. 278-287, 2004.
- [27] M. Rusiñol, D. Aldavert, R. Toledo, and J. Lladós, "Browsing Heterogeneous Document Collections by a Segmentation-free Word Spotting Method" in *ICDAR*, 2011.
- [28] S. N. Srihari, H. Srinivasan, C. Huang and S. Shetty, "Spotting Words in Latin, Devanagari and Arabic Scripts," in *Indian Journal of Artificial Intelligence*, vol. 16, pp. 2-9, 2006.
- [29] A. Papandreou, B. Gatos, G. Louloudis, and N. Stamatiopoulos, "Document image skew estimation contest," in *ICDAR*, pp. 1444-1448, 2013.
- [30] M. Kumar, M. K. Jindal and R. K. Sharma, "k -Nearest Neighbor Based Offline Handwritten Gurmukhi Character Recognition," in *International Conference on Image Information Processing*, 2011.
- [31] K. Riesen., S. Emmenegger, H. Bunke, " A novel software toolkit for graph edit distance computation. In: *Graph-Based Representations*," in *Pattern Recognition*, pp. 142-151, 2013.
- [32] K. Riesen, H. Bunke " Approximate graph edit distance computation by means of bipartite graph matching," in *Image and Vision Computing*, vol. 27, pp. 950-959, 2009.
- [33] J. L. Rothfeder, S. Feng and T. M. Rath, "Using corner feature correspondences to rank word images similarity," in *Computer Vision and Pattern Recognition Workshop*, pp. 30-35, 2003.