Classification of Historical Documents Based on LBP and LPQ Techniques

Pushpalata Gonasagi, Shivanand S Rumma, Mallikarjun Hangarge

Abstract: Historical documents are important source for knowing culture, language, social activities, educational system, etc. The historical documents are in different languages and evolved over centuries and transformed to present modern language, classification of documents into various eras, recognition of words etc. In this paper, we have proposed a new approach to automatic identification of the age of the historical handwritten document images based on LBP (Local Binary Pattern) and LPQ (Local Phase Quantization) algorithm. The standard historical handwritten document images named as MPS (Medieval Paleographic Scale) dataset which is publicly available is used to experiment. LBP and LPQ descriptors are used to extract the features of the historical document images. Further, documents are classified based on the discriminating feature values using classifiers namely K-NN (K-Nearest Neighbors) and SVM (Support Vector Machine) classifier. The accuracy of historical handwritten document images by K-NN and SVM are 90.7% and 92.8% respectively.

Keywords: LBP, LPQ, K-NN, SVM, Document Age, Historical Document.

I. INTRODUCTION

The historical documents are scientifically and culturally significant to the society. Since from the last decade, the experts digitize the historical documents and stored in the computer which we can accessed through the online anytime and anywhere. The digitized documents are enable us to access the information such as analyzing the documents, recognize the characters, words, retrieve the information, searching the information etc. Automatically identification of the age of document images using image processing and pattern recognition techniques is an important role. It helps historians, forensic science, institutional etc for fixing the authorship of the documents, establishment of the originality of the documents, solution to the questioned documents etc. The historical handwritten documents are studied by the archaeologists to identify the significant characteristics and their creators in order to date the documents [1].

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The documents lose their accessibility as sources, if documents were not having an accurate date of origin of the documents. The printed historical document images are used to estimate the unknown publication date from their scanned page images [2]. Most of the documents have not carried any explicit date information [3] which is difficult to decipher the authentic documents without knowing when they were composed. Usually historical documents have not carried the date before the period of 1600 CE [4]. If the historical documents don't have dates it is impossible to fix the authorship. So far very few works have been focused to identify the age of documents and remains it is a challenging problem. There is a lack of publicly available on the Kannada historical documents, so we have considered the online available standard historical handwritten document images for experiment and this dataset is in Medieval Dutch language. The documents are having different eleven classes from 1330 CE to 1550 CE. The age gap between the eleven classes of the historical document is 25 years. The association of the rest of paper is as per the following: We have reviewed on literature survey in section II. After that presents proposed method, introduction of historical handwritten documents, pre-processing and feature extraction techniques in section III. Then experiment and its results are discussed in section IV. Finally, section V provides the conclusion and future work.

II. RELATED WORK

We have reviewed many research works on identification of the age of the document. But here we have mentioned few literature survey reviews for documents age identification.
Sheng He et al. [5] discussed the scale-invariant features using MPS dataset. This system is used to form the stroke elements which enclosed the primary stroke of documents and proposed Evaluation of Self organizing (EOS) map to find the evolution of usual elements along the time for handwritten characters of the MPS dataset. They achieved an accuracy of 85.1% using KNN classifier. Sheng He et al. [6] explored the fragments of stroke and local contour. These strokes and local contour features are extracted and studied to determine for dating the historical documents. The strokes and local contour fragments explored using rotation invariant and scale features. These features are encoded into training code books using bag of words through classical model. They have achieved the 14.9 mean absolute errors which is optimal results. Halder et al. [7] article revealed the determination of ink age of printed documents. This system extracts the set of color features which are average intensities, pixel profile and kurtosis to analyze the ink age of the Google life magazine cover pages published in between 1930 to 1970 with having five decades different.

Classification of Historical Documents Based on LBP and LPQ Techniques

They designed neural net and trained to determine the ink age of unknown samples and achieved an accuracy of 74.5%. Raghunandan et al. [8] explored the method for classifications of handwritten documents using foreground and background information of identify the original and forgery documents. They have been analyzed Fourier Co-efficient to differentiate the documents as original and forgery. They have extracted the contrast features of the handwritten documents using Fourier Co-efficient to classify the documents as old and new. They have achieved an accuracy of 78.5% for new documents and 77.5% for old documents. Barboza et al. [9] demonstrated the method for estimating an age of the document using background information of RGB components of scanned document images. The documents were used by considered birth, wedding and other certificates during 20th century i.e period from 1913 to 1952. The document images considered age gap of one year from 1913 to 1952. They have applied the Gaussian distributions to normalized color components of the documents and considered the normalized color components for estimating the age of documents. Sheng He et al. [10] discussed PSD (Polar Stroke Descriptor). PSD are generated using rotation invariant local strokes features and also they have represents the stroke lets. The PSD and stroke lets are used to representing the stroke length in each direction with high-dimensional features for dating the historical documents. The documents are classified using K-NN classifier. They have achieved an accuracy of 60.7%. Fernando et al. [11] explored a model to date the historical color photographs. They have utilized the color components derivatives and angle features to extract the features of the photographs. They have used linear and nonlinear SVM classifier and achieved an accuracy of 85.5%.

III. PROPOSED METHOD

The objective is to present a new approach for identification of age of historical document images. The quality of the historical documents are degraded as increasing the age of documents and also depending on storage condition, humidity, environment and accessing the historical documents. Hence features are extracted using LBP and LPQ techniques from the historical document images. Further, we have classified the documents based on the different classes of historical handwritten document images using traditional classifiers using K-NN and SVM such as first class of historical document images belongs to 1300 class or remaining classes of the historical document images. The process of flow of proposed method is shown as block chart in **Fig. 1**.
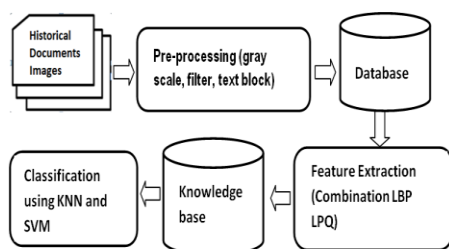

Fig.1 Block chart of the proposed method

A. Data Collection

Dataset: The standard dataset [12] are considered for the experiment. It contains historical handwritten document images during the period from 1300 CE to 1550 CE. The documents are charters which are particular sort of unequivocally dated documents broadly utilized within period of Medieval Ages to demonstrate a certain legitimates, financial activities, transactions had carried out. The historical document images are collected from four cities. The four cities are Leiden, Arhem, Leuven and Gronigen. The documents are explored numerous corners of the Medieval Dutch dialect. Besides, all the documents established and they have been written documents inside one of four cities. They took a few decades to notice that there is a gradual change in the scripts in handwriting habits. The historical handwritten document images include documents written around medieval years from 1300 CE to 1550 CE. Total eleven years of documents are considered for experiment. These eleven years of historical document are type of eleven classes and contained scanned documents in Portable Pix Map (PPM) format. The 1300 ± 5, 1325 ± 5, 1350 ± 5, 1375 ± 5, 1400 ± 5, 1425 ± 5, 1450 ± 5, 1475 ± 5, 1500 ± 5, 1525 ± 5, 1550 ± 5 with more or less five years of the documents are having limitations of the respective classes of the historical document images. The historical handwritten document images are contained currently **2858** documents as shown in **Table 1**. The text block of the historic handwritten document images are formed **4870**. The total numbers of fully covered texts from the text blocks are **2827** as shown in **Table 2**.

B. Pre-processing

Historical document images are not in condition to use directly for identification of the age of documents even though good scanners are available. The scanned historical document images are in high resolutions and also the presence of the unwanted marks due to ink blot, fading, poor quality of paper, noise are leads for misclassification of the historical document images. Hence we have performed the pre-processing step. In the pre-processing step, scanned color handwritten document images are converted into grayscale document images. Then we have applied Wiener filter for removal of blur from document images. The computational cost of LBP is high when features are extracted from high-resolution of the texture of the historical document images and hence this technique may unacceptable in practical image processing. So we have segmented the historical document images into text blocks of 512X512 sizes and retain only those text blocks which are completely covered text. The total number of handwritten document images and text blocks are discussed in the section III (A). The sample image of text block is shown in **Fig. 2.**
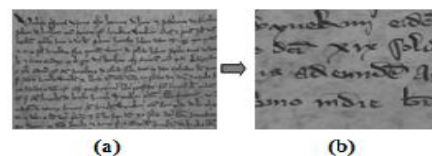

Fig. 2 (a) Sample original handwritten document image of 1300 CE (b) sample text block image on (a)

Table 1: Historical handwritten document images

Classes	1300	1325	1350	1375	1400	1425	1450	1475	1500	1525	1550
Pages	95	164	199	267	311	323	386	259	372	241	241

Table 2: Text blocks of historical handwritten document images

Classes	1300	1325	1350	1375	1400	1425	1450	1475	1500	1525	1550
Text blocks	281	281	146	192	234	272	304	199	298	298	322

C. Feature Extraction

The quality of the document images are measured using the texture of the document images. LBP and LPQ are the most efficient techniques to capture the texture of the document images and robust to the blur document images. Therefore, the features are extracted from the text blocks using the combination of the LBP and LPQ. For each text block 315 features are extracted. All eleven classes of the text block features are extracted and store as a knowledge base. The features are discriminating in a nature from one class to another class. The mathematical expression of LBP and LPQ techniques are as follows:

Local Binary Pattern: From [13,14], it is an efficient and straightforward texture descriptor that represents pixels of document images by threshold each neighborhood pixel and output is represented as a binary number. The extension of the LBP technique called as Uniform Local Binary Pattern and accessed to minimize the feature vector in terms of size. Uniform LBP is a rotation invariant descriptor. It is defined as pattern contains maximum two bitwise transitions from 0 to 1 or 1 to 0. The bitwise pattern is circularly traversed. If a binary pattern is 01110000 (2 transitions), then it is uniform and binary patterns 10001001 (4 transitions) and 010001010 (6 transitions) are not uniform. The Uniform binary patterns are utilized to compute LBP labels in order to that every uniform pattern has a separate label. By considered neighborhood parameters $p=8$ and $r=1$, it forms totally 256 patterns, among these pattern, uniform binary pattern are 58 and every non uniform binary pattern are codes with a single label. Therefore total 59 features are occurred.

From equation (1), the operator $LBP_{(p, r)}$ is used to study the local image texture in special domain. The symbol (p, r) is utilized for neighborhood pixels by indicating the p as sampling point in the direction of circle of radius r. Where gv_c be the gray value of the center pixel, gv_p be the gray value of p equal spaced neighboring pixels towards the direction of a circle of radius $(r > 0)$.

$$LBP_{(p, r)} = \sum_{p=0}^{p-1} f(gv_p - gv_c).2^p \tag{1}$$

$$where \quad f(k) = \begin{cases} 1, & k \geq 0 \\ 0, & k < 0 \end{cases}$$

Where 2^p is binomial factor which assigned to each sign of $f(gv_p - gv_c)$. From the definition of LBP operator, it is invariant versus any monotonic transformation of grayscale. It can be attained with sign of the differences instead of their exact values $(gv_p - gv_c)$.

The pattern which having maximum two transitions is measure as uniformity U. The uniform rotation-invariant texture and gray scale descriptor is expressed as in equation (2).

$$LBP_{(p,r)}^u = \begin{cases} \sum_{p=0}^{p-1} s(gv_p - gv_c) & if \quad U(LBP_{(p,r)}) \leq 2 \\ p+1, & Otherwise \end{cases} \tag{2}$$

Where

$$U\,LBP_{(p,\,r)} = \left| s(gv_{p-1} - gv_c) - s(gv_0 - gv_c) \right| + \sum_{p=1}^{p-1} \left| s(gv_{p-1} - gv_c) - s(gv_0 - gv_c) \right|$$

Local Phase Quantization (LPQ): From [15, 16], LPQ technique is extremely good tolerant to noise and outperforming for sharp and blurred document images. In another words LPQ descriptor is based on local phase spectrum which help to discriminates the underlying texture by distribution of different code words in the image region. So that it is an invariant property for the blur document images. The mathematical expression of the LPQ which yields blur image between original image $f(p, q)$ and blur image $g(p, q)$

$$g(p,q) = f(p,q) * h(p,q) + \eta(p,q) \tag{3}$$

Where $h(p, q)$ is the PSF (Point Spread Function) and $\eta(p, q)$ is additive noise. The symbol '*' indicates the two dimensional convolution. The relationship between $f(p, q)$ and $g(p, q)$ excluding noise within the Fourier frequency domain is expressed as in equation (4).

$$G(x, y) = F(x, y).H(x, y) \tag{4}$$

Where $G(x, y)$, $F(x, y)$, and $H(x, y)$ are the Fourier Transforms of $g(p, q)$, $f(p, q)$, and $h(p, q)$ respectively.
From equation (5), we have generated the phase information.

$$\angle G(x, y) = \angle F(x, y) + \angle H(x, y) \tag{5}$$

Where $\angle G(x, y)$, $\angle F(x, y)$, and $\angle H(x, y)$ are the phases of $g(p, q)$, $f(p, q)$, and $h(p, q)$ respectively.

If PSF is centrally symmetric, then the phase of $h(p, q)$ has only two values. It can be expressed as shown in equation (6).

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1536

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$$\angle H(x, y) = \begin{cases} 0, & if \quad H(x, y) \geq 0 \\ \pi, & Otherwise \end{cases} \quad (6)$$

Thus, the phase information is invariance between $G(x, y)$ and $F(x, y)$ can express as in equation (7).

$$\angle G(x, y) = \angle F(x, y), \quad for \quad all \quad H(x, y) \geq 0 \quad (7)$$

From equation (7), blur intensities absolutely holds between $g(p, q)$ and $f(p, q)$ from a phase perspective. The phase information is insensitive to centrally symmetric blur. LPQ executes using Short-Term Fourier Transform (STFT) to extracting phase information of every pixel. STFT is computed from the corresponding $M \times M$ neighborhood centered at the pixel as express in equation (8).

$$G(x, y) = \sum_{p \in N_p} \sum_{q \in N_q} g(p, q) \ e^{\frac{-j2\pi(xp + yq)}{M}} \quad (8)$$

Where Np and Nq are representing the neighborhood regions. By calculating at frequency points $x1 = (a, 0)$, $x2 = (0, a)$, $x3 = (a, a)$, and $x4 = (a, -a)$ using STFT, then LPQ extracts phase information. Where 'a' is a small value with relatively scalar which satisfies the equation (7) and assuring blur-insensitive. The obtained results are expressed by organizing as in equations (9) and (10).

$$W = [G(x1), G(x2), G(x3), G(x4)] \quad (9)$$

and

$$Z = [RE\{W\}, IM\{W\}] \quad (10)$$

Where $RE\{W\}$ and $IM\{W\}$ represent real and imaginary parts of W. Blur-insensitive textural information are collected to encode the elements in Z as in equation (11).

$$b = \sum_{n=1}^{8} m_i . 2^{i-1} \quad (11)$$

Where m_i is the quantization for i^{th} component in Z, given by equation (12).

$$m_i(p) = \begin{cases} 1, & Z_i(p) \geq 0 \\ 0, & Otherwise \end{cases} \quad (12)$$

Finally, 256 dimensional features are generated which are encoded values of b within image using formation of histogram.

LBP-LPQ descriptors: The features extracted from the LBP are 59 values and LPQ are 256 values. After combining the both descriptors values, it generated total 315 features values of each text block images of handwritten document images

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed system is evaluated by using handwritten text block images. The experiment is carried out using Image Processing Tool Matlab R2017a version. The experiments are carried out on the dataset as discussed in the section III (A). The Historical handwritten document images are collected during period 1300 CE to 1550 CE from the various cities as discussed in the section III(A). The original historical handwritten document images are color document images. The sample image is shown in **Fig. 4(a).** These documents are converted into grayscale document images and enhanced by the Wiener filter method. The enhanced document images are segmented into 512 x 512 text blocks and retained only text blocks which are covered by full text as discussed in section III(B) and sample images are shown in **Fig. 4(b).** As discussed in the section III(C), features are extracted by applying the combination of LBP and LPQ methods to all eleven classes of the text blocks. Total 315 features are generated for each block images of the class and stored them as a knowledge base. Finally, we have identified the age of text blocks of handwritten document images by using classifier namely K-NN [17] and SVM [18]. The outcome of the experiment is measured in terms of the classification rate. The accuracy of the classification of the proposed method using K-NN and SVM is shown in **Table 3.** The SVM classifier has shown high results compared to KNN classifier. We have attained the average accuracy of 90.5% using K-NN classifier and 92.8% using SVM classifier. It can be realized from the confusion matrix of K-NN and SVM classifiers are shown in **Table 4** and **Table 5** respectively. We have compared our results with the recently published work in the literature [5] is shown in **Table 6.** It reveals that proposed method is performing better than the reported method.
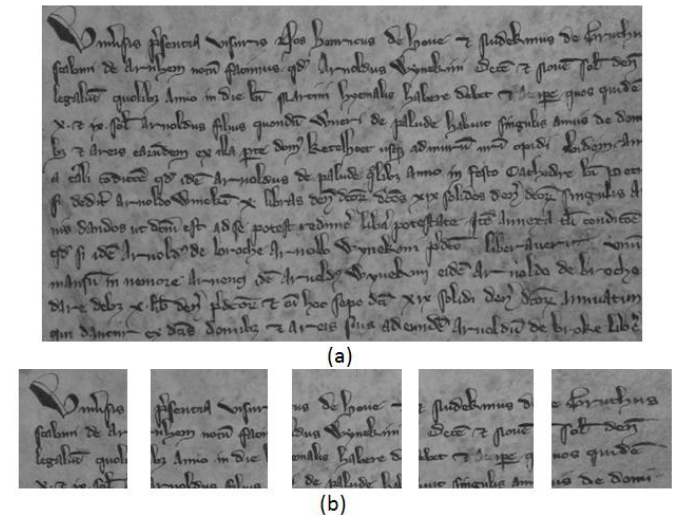

(a)

(b)

Fig. 4 (a) Sample original historical handwritten document image of class 1300 CE (b) Text block sample of segmentation of size 512×512 on (a).

V. CONCLUSION AND FUTURE WORK

In this paper, we have presented a new algorithm for automatic identifying of the age of the given historical document image based on the texture attributes using a hybrid method by combining LBP and LPQ methods. The traditional KNN and SVM classifiers are

Table 3: The accuracy for classification of the proposed method using classifier (K-NN and SVM)

Classes (Handwritten documents in the period(CE))	KNN Classifier		SVM Classifier	
	Classification rate of document identification (%)	Error rate (%)	Classification rate of document identification (%)	Error rate (%)
1300	94.3	5.7	94.3	4.7
1325	94.0	6.0	94	6.0
1350	91.8	8.2	95.9	4.2
1375	89.6	10.4	91.2	8.8
1400	92.8	7.2	92.3	7.7
1425	90.4	9.6	91.2	8.8
1450	94.1	5.9	95.4	4.6
1475	83	17.0	91	9.0
1500	87.2	12.8	88.3	11.7
1525	81.5	18.5	92	8.0
1550	96.9	3.1	95.7	4.3
Average Accuracy	**90.5**	**9.5**	**92.8**	**7.2**

Table 4 Confusion matrix using K-NN classifier

Years	1300	1325	1350	1375	1400	1425	1450	1475	1500	1525	1550
1300	**265**	3	2	1	1	6	2	1	-	-	-
1325	8	**264**	-	2	2	1	1	2	-	-	1
1350	7	1	**134**	-	-	-	1	-	1	3	-
1375	1	1	-	**172**	2	-	3	7	2	2	2
1400	-	3	-	3	**217**	1	3	4	-	1	2
1425	6	3	-	4	1	**246**	1	8	-	3	-
1450	2	2	-	2	1	4	**286**	3	2	1	1
1475	2	4	-	5	6	5	1	**165**	5	4	2
1500	-	4	-	1	4	4	8	5	**260**	11	1
1525	2	6	-	6	4	1	3	12	8	**243**	13
1550	-	2	1	-	-	2	1	-	3	1	**312**

Table 5: Confusion matrix using SVM classifier

Years	1300	1325	1350	1375	1400	1425	1450	1475	1500	1525	1550
1300	**265**	5	-	-	-	6	2	2	-	1	-
1325	6	**264**	-	1	4	3	-	1	1	-	1
1350	-	-	**140**	-	1	1	-	-	1	3	-
1375	1	4	-	**175**	4	-	2	5	-	1	-
1400	-	1	-	7	**216**	2	5	-	3	-	-
1425	5	1	-	-	1	**248**	7	6	4	-	-
1450	-	-	3	2	-	2	**290**	2	-	3	2
1475	-	2	-	-	2	4	2	**181**	4	4	-
1500	-	-	-	1	3	-	10	9	**263**	9	3
1525	-	1	-	1	4	-	3	6	4	**274**	5
1550	-	-	-	-	-	2	2	2	6	2	**308**

Table 6: Comparison for performance of the proposed method

Author	Dataset	Accuracy (%)
Sheng He [5]	MPS dataset	85.1%
Proposed Approach	MPS dataset	92.8%

used to classify eleven classes based on their originality of the classes to which it's belong. The proposed features extraction method is simple, low computational requirements and high quality description of huge datasets. We have explored the LBP and LPQ descriptors which help in finding the difference between the classes of the historical document images. In the other words, generated discriminative features values of all classes and classifying the documents most efficiently. It is helpful to historians to fix the period or origin of the documents. The future task would to be validating the proposed method by reducing the age gap of historical handwritten document and based on writing styles of handwritten documents.

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