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WRITER IDENTIFICATION BY TEXTURE ANALYSIS BASED ON KANNADA HANDWRITING

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Abstract—Writer identification problem is one of the important area of research due to its various applications and is a challenging task. The major research on writer identification is based on handwritten English documents with text independent and dependent. However, there is no significant work on identification of writers based on Kannada document. Hence, in this paper, we propose a text-independent method for off-line writer identification based on Kannada handwritten scripts. By observing each individual's handwriting as a different texture image, a set of features based on Discrete Cosine Transform, Gabor filtering and gray level co-occurrence matrix, are extracted from preprocessed document image blocks. Experimental results demonstrate that the Gabor energy features are more potential than the DCTs and GLCMs based features for writer identification from 20 people.

Keywords- DCT, Gabor filter, Gabor energy, texture, gray level co-occurrence matrix, writer identification.

I. INTRODUCTION

One of the means of identifying an individual is through his/her handwriting pattern, since there exists a certain degree of stability in the pattern of an individual's writing style, by which it is possible to identify the author. The applications are many like forensic science, library archival, authorship determination of historical manuscripts to be able to do their indexing and retrieval etc. The research on Writer identification problem can be focused on two streams, off-line and on-line writer identification. In offline writer identification only handwritten scanned image will be available without any temporal information. Further offline writer identification can be done using text-dependent and text-independent methods. The earlier research was focused on text-dependent methods of writer identification, where the two writers samples are compared based on the fixed text. Text-dependent methods are not popular in practical applications; hence there is a need to develop text-independent method for writer identification. Text independent offline writer identification is more challenging than online writer identification. Another traditional classification of writer identification methods is into global and local approaches. The global approach are based on the overall look and feel of the writing, on the other hand, local approach identify the writer based on localized features of writing, which are inherent in a way writer specifically writes the characters using allograph level, graphemes level features[1]. Text dependent method is to check a person's handwriting with two or more text materials with the same contents. It is very relevant with the text contents and we can utilize font, word position, istribution of strokes orientation, strokes arrangement as its

characteristics. Some text dependent methods ave been widely used, such as orthogonal transform, histogram method, standard template transform, higher-order moments correlation, orientation index histogram and strokes matching, etc. But in text independent writer identification problem, we can not utilize the above features are not suitable. Hence it is much more difficult problem. Recently, a number of new approaches to writer identification have been proposed in the literature. In [4] the problem of writer verification by casting it as a classification problem with two classes, authorship and non-authorship is addressed. In [5] approach was based on single words by morphologically processing horizontal projection profiles. In [6] a writer identification system to extract a set of features from a text line to determine the author is described. Edge-based directional probability distributions and connected component contours as features for the writer identification task are proposed in [7,8,9]. Graphemes were introduced as features for describing the individual properties of handwriting [10, 11]. In [12] a set of eleven features which can be extracted easily and used for the identification and verification of documents containing handwritten digits is presented. The individuality of handwriting by extracting a set of macro (global) and micro (local) features is established in [13]. In principle any texture analysis technique [14] can be applied to the uniform text blocks. Texture features based on the co-occurrence histograms of wavelet decomposed images are extracted for off-line writer identification based on English and Kannada handwriting, which are text-independent in [15]. The textures (Kannada script images) are decomposed using Empirical mode decomposition, which in turn generates series of intrinsic mode functions for writer identification of

Kannada handwriting is shown in [16]. Combining the texture level and allograph level features is known to improve the identification results [17]. In this paper, three methods are implemented to obtain texture features based on DCT, Gabor filter, and GLCM of the image of Kannada document. The DCT, Gabor filtering are becoming popular now and the GLCMs are widely recognized as the benchmark technique in texture analysis. The paper is organized as follows: In Section II, data collection and preprocessing, Section III contain the texture feature extraction from the DCT, Gabor transformed and Co-occurrence matrix of input Kannada document image are reported. The training and classification phases are explained in Section

IV. In Section V, the results of writer identification from handwritten document images are discussed in detail. Finally, Section VI contains conclusion.

II. DATA COLLECTION AND PREPROCESSING

A. Kannada

Kannada is one of the popular languages in India. Kannada script writing system is alphasyllabary in which all consonants have an inherent vowel. Other vowels are indicated with diacritics, which can appear above, below, before or after the consonants. Kannada has 16 vowels and 34 consonants. There are about 250 basic, modified and compound character shapes in Kannada. Writing style is from left to right in a horizontal manner. Upper and lower case distinction is not present in Kannada. It is not like the English words which are only constructed by 26 letters.

B. Data Collection

As document image database of Kannada language is currently not available. We have created our own dataset. First, the handwritten documents are collected from 20 writers irrespective of age groups and professions, as one document per writer. The collected documents are scanned through scanner HP Scanjet G2410 to obtain digitized images. The scanning is performed in normal 100% view size at 150 dpi resolution. The 20 blocks are segmented manually from the scanned document image of each writer. The size of the block was considered is 256X256 pixels. Hence the database size is 400 blocks. For each writer 10 blocks are used for training and remaining 10 blocks for testing. Sample blocks of 3 different writers are shown in Fig. 1.

ಇಂಜಿನಿಯರಿಂಗ್ ನೇರ ಪ್ರತಿರೋಧಕ ಬರಹವು ನೋಡಲು ಕೆ.ಎ. * ಸುಗಂಧ ಎಣ್ಣೆ ಕೆ.ಎ. * ಅಂತಿಮ ಫಿಲಂ ಕೆ.ಎ. * ಸುಗಂಧ ಎಣ್ಣೆ	ಇಂಜಿನಿಯರಿಂಗ್ ನೇರ ಪ್ರತಿರೋಧಕ ಬರಹವು ನೋಡಲು ಕೆ.ಎ. * ಸುಗಂಧ ಎಣ್ಣೆ ಕೆ.ಎ. * ಅಂತಿಮ ಫಿಲಂ ಕೆ.ಎ. * ಸುಗಂಧ ಎಣ್ಣೆ	ಮೂಲಕ ಇಂಜಿನಿಯರಿಂಗ್ ನೇರ ಪ್ರತಿರೋಧಕ ಬರಹವು ನೋಡಲು ಕೆ.ಎ. * ಸುಗಂಧ ಎಣ್ಣೆ ಕೆ.ಎ. * ಅಂತಿಮ ಫಿಲಂ ಕೆ.ಎ. * ಸುಗಂಧ ಎಣ್ಣೆ
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Figure 1. Sample blocks of size 256x256 of three different writers

C. Preprocessing

Any writer identification system for better performance requires noise and skew free images. We employed preprocessing steps such as removal of non-text regions, skew correction, noise removal and binarization. In the proposed model, text portion of the document image was separated from the non-text region manually. A global threshold approach [21] is used to binarize the scanned gray scale images where black pixels having the value 0's correspond to object and white pixels having value 1's correspond to background. A sample of original document image, extracted block of size 256 x 256 pixels, and binarized image is shown in Fig. 2.

‘ಫಸ, ಕನಕಗು, ಮುಖ್ಯವಾಗಿ ಬರಹವು ನೋಡಲು
ಕಾಣಿಸಿಕೊಳ್ಳುತ್ತದೆ. ಇಂತಹ ಸೇವೆ, ಸಹಕಾರ ಹೀಗಾಗಿ, ಹಿಂಥ ಸೇವೆ.
- ಲಿಂಗಿ ಬಿಲಿಗಿಲ್ಲದೆ ಬೇರೆ, ಇದ್ದು ರೇಖಿಸಿಬಿಡುಗಟ್ಟುವು, ನಿಶಿತರ
ನಿಶಿತರೊಡನೆ ಇದ್ದು, ಕೂಡ ನಡೆಸಲು ನಿಶಿತರಾಗು.
- ಬರಹವು, ಬರಹವೇನೂ ಬೇರೆ, ಸೇವೆಯಾದುದ್ದರಿಂದ ಹಿಂಥ
ರೀತಿ ನಿಶಿತರ ಸೇವೆ ಬರಹವು ಬರಹವು ನಿಶಿತರ ಬರಹವು,
ಕೂಡ ಕೂಡ ನಿಶಿತರೊಡನೆ ಇದ್ದು, ಹಿಂಥ ಬರಹ
ಕೂಡ ಕೂಡ, ನಿಶಿತರೊಡನೆ ಬರಹವು ಕೂಡ ಕೂಡ, ಬರಹ
ಬರಹವು, ನಿಶಿತರೊಡನೆ ಬರಹವು ಬರಹವು, ಬರಹ
ಬರಹವು, ನಿಶಿತರೊಡನೆ ಬರಹವು ಬರಹವು, ಬರಹ
ಬರಹವು, ನಿಶಿತರೊಡನೆ ಬರಹವು ಬರಹವು, ಬರಹ

ಬರಹವು ಬರಹವು ಬರಹವು ಸೇವೆಯ ಬರಹವು ಬರಹವು
ಕೂಡ ನಿಶಿತರೊಡನೆ, ಬರಹವು ಸೇವೆಯ ಬರಹವು
ಬರಹವು - ಬರಹವು ಬರಹವು ಬರಹವು, ಬರಹವು ಸೇವೆಯ
ನಿಶಿತರೊಡನೆ ಬರಹವು, ನಿಶಿತರೊಡನೆ ಬರಹವು ಕೂಡ ಕೂಡ, ಬರಹ
ಬರಹವು - ನಿಶಿತರೊಡನೆ ಬರಹವು ಬರಹವು ಬರಹವು ಬರಹವು
ಬರಹವು ಬರಹವು ಬರಹವು ಬರಹವು ಬರಹವು ಬರಹವು
ಬರಹವು ಬರಹವು ಬರಹವು ಬರಹವು ಬರಹವು ಬರಹವು
ಬರಹವು ಬರಹವು ಬರಹವು ಬರಹವು ಬರಹವು ಬರಹವು
ಬರಹವು ಬರಹವು ಬರಹವು ಬರಹವು ಬರಹವು ಬರಹವು
ಬರಹವು ಬರಹವು ಬರಹವು ಬರಹವು ಬರಹವು ಬರಹವು

Figure 2. (a) Original document image (b) Extracted block of size of size

256 x 256 pixels (c) Binarized image

The preprocessing is achieved by using morphological filters. It should be noted that the text block might contain lines and variable spaces between lines, words and characters including numerals. Proposed algorithm outperforms even with such complex text block without normalization.

III. TEXTURE FEATURE EXTRACTION

A. Discrete Cosine Transform

The discrete cosine transform (DCT) concentrates the information content in a relatively few coefficients. The DCT is purely real. The DCT expresses a sequence of finitely many data points in terms of a sum of cosine functions oscillating at different frequencies that are necessary to preserve the most important features. With an input image, A_{ij} , the DCT coefficients for the transformed output image, $B(p,q)$, are computed according to equation (1). In the equation (1), A is the input image of size m -by- n pixels, A_{ij} is the intensity of the pixel in row m and column n of the image and $B(p,q)$ is the DCT coefficient in row p and column q of the DCT matrix.

For an image $A(i, j)$, the DCT coefficient matrix $B(p, q)$ is given by

$$B(p, q) = \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} A_{ij} \cos\left(\frac{\pi(2i+1)}{2m} p\right) \cos\left(\frac{\pi(2j+1)}{2n} q\right) \quad (1)$$

where m and n are the number of rows and columns of the image matrix; p and q are the frequency indices along the i and j directions, respectively. We have applied DCT on image A , the resulting DCT image is divided into 8 parts, then standard deviation of each part is taken, this forms the feature vector. The process is shown in Fig. 3 below.

Figure 3. Eight features of DCT image

B. Gabor filter

Psychological research has shown evidence that the human brain does a frequency analysis of the image[3]. Gabor filters have been shown to be a good model of the processing that takes place in the human visual cortex, and have been used successfully in both texture segmentation [14] and texture classification [2]. The text area contains high frequency components. This property which we have exploited while taking Gabor filter bank approach. These filters are designed to take care of this property [19, 20]. A 2D Gabor filter $g(x, y)$ can be formulated as:

$$g_{\lambda, \theta, \psi}(x, y) = e^{-\frac{(x'^2 + y'^2)}{2\sigma^2}} \cos(2\pi \frac{x'}{\lambda} + \psi) \quad (2)$$

$$\text{where } \begin{aligned} x' &= x \cos \theta + y \sin \theta, \\ y' &= -x \sin \theta + y \cos \theta \end{aligned}$$

We employ two dimensional Gabor filters to extract the features from input text block image to identify the writer from 20 writers. The preprocessed input binary image is convolved with Gabor filter considering valid values of real numbers between 0 and 360, we take four different orientations (0° , 45° , 90° and 135°) and the wavelength λ of the cosine factor, valid values are real

numbers equal to or greater than 2, we use five different wavelengths ($\lambda=2, 4, 8, 16$ and 32) and $\sigma=0.56\lambda$

with the half-response spatial frequency bandwidth b ($= 1$ octave). In order to prevent the occurrence of undesired effects at the image borders, the wavelength value should be smaller than one fifth of the input image size. Valid values of phase offset ψ are real numbers between -180 and 180 . The values 0 and 180 correspond to center-symmetric 'center-on' and 'center-off' functions, respectively, while -90 and 90 correspond to anti-symmetric functions. All other cases correspond to asymmetric functions. The spatial frequency f is related to λ , by the relation $f=1/\lambda$. For the handwriting image I , the Gabor representation of a handwriting is the convolution of the handwriting image with the Gabor filter and is defined below:

$$r_{\lambda, \theta, \psi}(x, y) = \iint I(\epsilon, \eta) g(x-\epsilon, y-\eta) d\epsilon d\eta$$

C. Gabor-Energy

The filter results of a symmetric and an antisymmetric filter can be combined in a single

quantity which is called the Gabor-Energy. For writer identification, we have considered the Gabor energy associated with the filter in the writer's image block. Here we have exploited the Gabor energy associated with the handwriting style property of the writers. This feature is related to a model of so called complex cells in the primary visual cortex [18, 19] and is defined in the following way:

$$E_{\lambda, \theta} = \sqrt{r_{\lambda, \theta, 0}^2 + r_{\lambda, \theta, -\frac{\pi}{2}}^2} \quad (4)$$

Where $E_{\lambda, \theta}$ is Gabor Energy, $r_{\lambda, \theta, 0}$ and $r_{\lambda, \theta, -\frac{\pi}{2}}$ are

the responses of the linear symmetric and antisymmetric Gabor filters, respectively. Combining the symmetric and antisymmetric filter banks described in above results in a new, non-linear filter bank of 20 channels with the same coverage of the spatial frequency domain. Since a Gabor filter is obtained by modulating a sinusoid with a Gaussian, whose main features are mean and standard deviation, we use in this paper standard deviation as means to calculate feature vector.

D. Gray Scale Co-occurrence Matrices (GSCM)

A statistical method that considers the spatial relationships of pixels is the Gray-Scale Co-occurrence Matrices (GSCM) of the image, also known as the gray-level spatial dependence matrix. We use only one distance $d = 1$ and four directions $\theta = 0^\circ, 45^\circ, 90^\circ, 135^\circ$ to construct four GSCMs. For one matrix 3 features each i.e., correlation, contrast and homogeneity are extracted, so totally 12 features for each image block.

IV. TRAINING AND CLASSIFICATION

A. Training Algorithm

The three feature extraction algorithms are described in the following:

Algorithm 1:

Input: Preprocessed image block of size 256X256 pixels.

Output: Feature vector of size 8.

- Apply DCT on preprocessed image and divide the magnitude of DCT image into horizontally, vertically and diagonally to get 8 equal non-overlapping parts A, B, C, D, E, F, G, H and extract the local features by computing the standard deviation of all 8 parts as std1, std2, std3, std4, std5, std6, std7, std8. This forms 8 features. The process of feature extraction is shown in above Fig. 3.
- Store all the 8 computed features in a vector.

Method 2:

Input: Preprocessed image block of size 256X256 pixels.

Output: Feature vector of size 60 is computed.

- Apply Gabor filter to preprocessed image. We get symmetric Gabor filter response $r_{\lambda_i, \theta_j, 0}$, antisymmetric Gabor filter response $r_{\lambda_i, \theta_j, -\frac{\pi}{2}}$ and Gabor Energy E_{λ_i, θ_j} . Here $\lambda_i = 2^i$ and

$$\theta_j = (j-1)\frac{\pi}{4} \text{ for } i=1..5, j=1..4. \text{ Refer Eqn}$$

(3) and (4). Compute the Standard Deviation of each $r_{\lambda_i, \theta_j, 0}$, $r_{\lambda_i, \theta_j, -\frac{\pi}{2}}$ and E_{λ_i, θ_j} , the

resulting vectors we denote as RP1, RP2 and GE vectors respectively in this paper. Each vector is of size 20. This forms 60 features.

- Store all the 60 computed features in a vector.

Method 3:

Input: Preprocessed image block of size 256X256 pixels. Output: Feature vector of size 12.

- For Gray Level Co-occurrence Matrix of preprocessed image, obtain properties correlation, Contrast, Homogeneity vectors for 4 directions 0, 45, 90 and 135 for distance $d=1$ and calculate standard deviation of each vector.
- Store all the 12 computed features in a vector.

B. Classification

One mostly used classifier Nearest Neighbor classifier (K-NN) for the purpose of writer identification. KNN classifier is adopted for identification purpose. This method is well-known non-parametric classifier, where posterior probability is estimated from the frequency of nearest neighbors of the unknown pattern. The key idea behind k-nearest neighbor classification is that similar observations belong to similar classes. The test image is classified to a class, to which its k-nearest neighbor belongs to. Feature vectors stored priori are used to decide the nearest neighbor of the given test image feature vector. Images in the training set the determination stage. During the training phase, features are extracted from the training set by Algorithm 1. These features are input to K-NN classifier to form a knowledge base that is subsequently used to classify the test images. During test phase, the test image whose writer is to be recognized is preprocessed in a similar way as described in Section II(C) and features are computed performing the Algorithm 1. The Euclidean distances between the test feature vector with that of

the stored features are obtained to identify the k-nearest neighbor. Finally, the classifier assigns the test image to a class that has the minimum distance with voting majority. The corresponding block is declared as recognized writer. The process of training and writer identification phase is shown in Fig. 4.

Figure 4. Writer Identification System (a) Training Phase (b) Writer Identification Phase

V. EXPERIMENTAL RESULTS

The proposed method is used to train 50% block images and 50% block images for testing. The 3 different methods proposed are based on the texture features extracted by applying DCT, Gabor, GLCM and are stored separately as different feature sets. KNN classifier is used for classification of the writers. The identification accuracy of the proposed DCT based (Algorithm 1) which has feature vector of size 8 is 77%. In Gabor based (Algorithm II) if only Gabor energy vector (GE) is considered (20 features) it is 85.5%, if symmetric Gabor filter response vector RP1 and GE vector (40 features) are considered the accuracy is 84%, if antisymmetric Gabor filter response RP2 and GE vector (40 features) are considered the accuracy is 88.5%, but if all vectors RP1, RP2 and GE (60 features) are considered the accuracy is 82%. GLCM based (method 3) which has feature vector of size 12 is 79.5%. The proposed algorithm was implemented using MATLAB R2009a. The Gabor energy based features proved to be more accurate than the GLCMs, and DCTs producing results of 88.5% accuracy. The experimental results of different these three methods is shown in Table 1 and the chart of Feature Set Vs Writer Identification Rate is shown in Fig. 5.

Vs Writer identification Rate is shown in Fig. 5.

TABLE I. EXPERIMENTAL RESULTS OF DCT, GABOR, GLCM FEATURES

Writer Identification	DCT, GABOR, GLCM FEATURES Vs IDENTIFICATION RATE		
	Method	Features	Identification Rate %
DCT		Std1....Std8	77
Gabor		GE	85.5
		RP1,GE	84
		RP2+GE	88.5
		RP1, RP2, GE	82
GLCM		Correlation, Contrast, Homogeneity	79.5

F1 : Std1 ... Std8	}	DCT features
F2 : GE		
F3 : RP1+GE	}	Gabor features
F4 : RP2+GE		
F5 : RP1+RP2+GE		
F6 : Correlation, Contrast, Homogeneity	}	GLCM features

Figure 5. Feature Set Vs Writer Identification Rate

VI. CONCLUSION

The Gabor energy features are proved to outperform the DCTs and GLCMs based features. No character segmentation or connected component analysis is required. The presence of numerals may affect the identification rate to little extent. The method is not complicated - simple, established texture classification techniques have been employed. Although scaling and normalization of document is not done, encouraging results are obtained, so scaling

and normalization may further enhance the writer identification rate. The experimental results demonstrate the efficacy of the proposed methods and the potential of such global approaches for the writer identification in the document image analysis, which has significance in biometrics and forensic science. Future work will involve extensions of above outlined methods, taking into consideration more number of writers.

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