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Global Approach for Script Identification using Wavelet Packet Based Features

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Abstract

In a multi script environment, an archive of documents having the text regions printed in different scripts is in practice. For automatic processing of such documents through Optical Character Recognition (OCR), it is necessary to identify different script regions of the document. In this paper, a novel texture-based approach is presented to identify the script type of the collection of documents printed in seven scripts, to categorize them for further processing. The South Indian documents printed in the seven scripts - Kannada, Tamil, Telugu, Malayalam, Urdu, Hindi and English are considered here The document images are decomposed through the Wavelet Packet Decomposition using the Haar basis function up to level two. Gray level co-occurrence matrix is constructed for the coefficient sub bands of the wavelet transform. The Haralick texture features are extracted from the co-occurrence matrix and then used in the identification of the script of a machine printed document. Experimentation conducted involved 2100 text images for learning and 1400 text images for testing. Script classification performance is analyzed using the K-nearest neighbor classifier. The average success rate is found to be 99.68%.

Keywords: *Document processing, Wavelet packets, Feature extraction, Script identification.*

1. Introduction

The progress of information technology and the wide reach of the Internet are drastically changing all fields of activity in modern days. As a result, a very large number of people would be required to interact more frequently with computer systems. To make the man–machine interaction more effective in such situations, it is desirable to have systems capable of handling inputs in a variety of forms such as printed/handwritten paper documents. If the computers have to efficiently process the scanned images of printed documents, the techniques need to be more sophisticated. Even though computers are used widely in almost all the fields, undoubtedly paper documents occupy a very important place for a longer period. Also, a large proportion of all kinds of business writing communication exist in physical form for various purposes. For example, to fax a document, to produce a document in the court, etc. Therefore, software to automatically extract, analyze and store information from the existing paper form is very much needed for preservation and access whenever necessary. All these processes go under the title of document image analysis, which has received significance as a major research problem in the modern days.

Script identification is an important problem in the field of document image processing, with its applications to sort document images, as pre processor to select specific OCRs, to search online archives of document images for those containing a particular language, to design a multi-script OCR system and to enable automatic text retrieval based on script type of the underlying document.

Automatic script identification has been a challenging research problem in a multilingual environment over the last few years. All existing works on automatic language identification are classified into either local approach or global approach. Ample work has been reported in literature using local approaches [1-8]. The local features are extracted from the water reservoir principle [1, 3], morphological features [4], profile, cavities, corner points, end point connectivity [7], top and bottom profile based features [5, 8]. In local approaches, the features are extracted from a list of connected components such as line, word and character, which are obtained only after segmenting the underlying document image. So, the success rate of classification depends on the effectiveness of the pre-processing steps namely, accurate Line, Word and Character segmentation. It sounds paradoxical as LWC segmentation can be better performed, only when the script class of the document is known. Even when the script classes are known from the training data, testing requires the performance of LWC segmentation prior to script identification. But, it is difficult to find a common segmentation method that best suits for all the script classes. Due to this limitation, local approaches cannot meet the criterion as a generalized scheme.

In contrast, global approaches employ analysis of regions comprising of at least two text lines and hence fine segmentation of the underlying document into line, word and character, is not necessary. Consequently, the script classification task is simplified and performed faster with the global approach than the local approach. So, global schemes can best suited for a generalized approach to the script identification problem. Satisfactory work has been reported in literature using global approaches [9-18]. Global approaches make use of the texture-based features. These texture features can be extracted from a portion of a text region that may comprise of several text lines.

Texture could be defined in simple form as “repetitive occurrence of the same pattern”. Texture could be defined as something consisting of mutually related elements. Another definition of texture claims that, “an image region has a constant texture if a set of its local properties in that region is constant, slowly changing or approximately periodic”. Texture classification is a fundamental issue in image analysis and computer vision. It has been a focus of research for nearly three decades. Briefly stated, there are a finite number of texture classes C_i, i = 1, 2, 3, n. A number of training samples of each class are available. Based on the information extracted from the training samples, a decision rule is designed, which classifies a given sample of unknown class into one of the n classes [13]. Image texture is defined as a function of the spatial variation in pixel intensities. The texture classification is fundamental to many applications such as automated visual inspection, biomedical image processing, content-based image retrieval and remote sensing. One application of image texture is the recognition of image regions using texture properties. From the literature survey, it is observed that sufficient work has been carried out using texture features. Existing methods on Indian script identification use the texture features extracted from the co-occurrence matrix, wavelet based co-occurrence histogram [12], Gabor filters [20]. Very few works are reported on script identification particularly using wavelet transform based features [12]. In this paper, the features useful for script identification are extracted from the wavelet packets decomposition. As such, no work has been reported that uses the wavelet packet based features for script identification.

The rest of the paper is organized as follows. The Section 2 describes about the wavelet packet transform. The database constructed for testing the proposed model is presented in Section 3. Section 4 discusses the necessary preprocessing steps. In Section 5, complete description of the proposed model is explained in detail. The experimental results obtained are presented in section 6. Conclusions are given in section 7.

2. Wavelet Packet Transform (WPT)

Research interest in wavelets and their applications has grown tremendously over the past few years. It has been shown that wavelet-based methods continue to be powerful mathematical tools and offer computational advantage over other methods for texture classification. The different wavelet transform functions filter out different range of frequencies (i.e. sub bands). Thus, wavelet is a powerful tool, which decomposes the image into low frequency and high frequency sub band images.

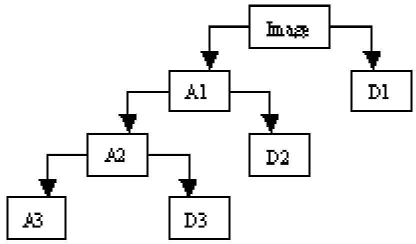
The Continuous Wavelet Transform (CWT) is defined as the sum over all time of the signal multiplied by scaled, shifted versions of the wavelet function ψ:

$$C(scale, position) = \int_{-\infty}^{-\infty} f(t)\psi(scale, position, t)dt \qquad (1)$$

The results of the CWT are many wavelet coefficients C, which are functions of scale and position. The wavelet transform decomposes a signal into a series of shifted and scaled versions of the mother wavelet function. Due to time frequency localization properties, discrete wavelet and wavelet packet transforms have proven to be appropriate starting point for classification tasks. In the 2-D case, the wavelet transform is usually performed by applying a separable filter bank to the image. Typically, a low filter and a band pass filter are used. The convolution with the low pass filter results in the approximation image and the convolutions with the band pass filter in specific directions result in the detail images.

In the simple wavelet decomposition, only the approximation coefficients are split iteratively into a vector of approximation coefficients, and a vector of detail coefficients are split at a coarser scale. That means, for an n-level decomposition, n+1 possible ways of decomposition are obtained as shown in Figure 1. The successive details are never reanalyzed in the case of simple wavelet decomposition.

The concept of wavelet packets was introduced by Coifman et.al. [23]. In wavelet packets, each detail coefficients vector is also decomposed as in approximation vectors. The recursive splitting of both approximate and detail sub images will produce a binary tree structure as shown in Figure 2.



$$\begin{aligned}\text{Image} &= A1 + D1\\ &= A2 + D2 + D1\\ &= A3 + D3 + D2 + D1\end{aligned}$$

Figure 1. Wavelet Decomposition Tree

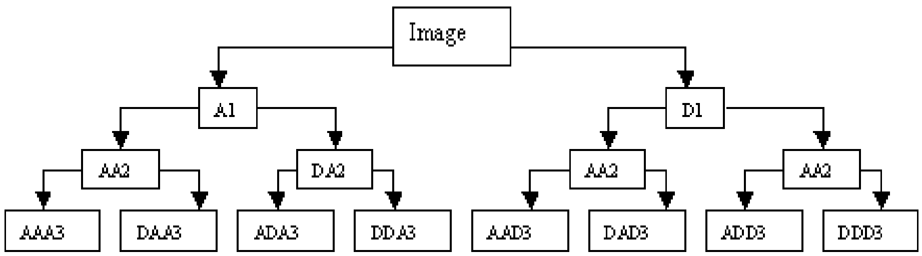


Figure 2. Wavelet Packet Decomposition Tree.

In the case of wavelet, the coefficients of only the approximate sub band are used as the features, whereas in the case of wavelet packets, the coefficients of both approximate and detail sub bands are used as the features. The features derived from a detail images uniquely characterize a texture. The combined transformed co-efficients of the approximate and detail images give efficient features and hence could be used as essential features for texture analysis and classification. A set of decomposed sub bands that yield useful feature values are selected from the wavelet packet tree. The features obtained from the set of sub bands from the transformed images are used for texture classification and are discussed in Section 5.

3. Data Collection

Standard database of documents of Indian languages is currently not available. In this paper, it is assumed that the input data set contains text blocks of the seven scripts - Kannada, Tamil, Telugu, Malayalam, Urdu, Hindi and English, followed in South Indian states. For the proposed model, two sets of database were constructed, one database for learning and the other to test the system. The database of size 300 images for learning and 200 images for testing were used from each of the seven scripts. The text blocks of Kannada and English scripts were created using the Microsoft word software. These text blocks were imported to the Micro Soft Paint program and saved as black and white bitmap (BMP) images. The font type of Times New Roman, Arial, Bookman Old Style and Tahoma were used for English language. The font type of Bharaha and Shrilipi were used for Kannada language. The font size of 14, 20 and 26 were used for both Kannada and English text words. However, the performance is independent of font size. The text blocks of Tamil, Telugu, Malayalam, Urdu and Hindi scripts were constructed by clipping only text portion of the document downloaded from the Internet. The size of the text block was considered as 600x600 pixels.

One more data set constructed from the scanned document images was used to test the proposed model. The printed documents like newspapers and magazines were scanned through an optical scanner to obtain the document image. The scanner used for obtaining the digitized images is HP Scan Jet 5200c series. The scanning is performed in normal 100% view size at 300 dpi resolution. The image of size 600x600 pixels was considered such that at least 40% of the image contains text region. The test data set constructed from the scanned images involved 100 samples from each of the seven scripts.

4. Preprocessing

Any script identification method used for identifying the script type of a document, requires conditioned image input of the document, which implies that the document should be noise free, skew free and so on. In this paper, the preprocessing techniques such as noise removal and skew correction are not necessary for the manually constructed data sets. However, for the datasets that were constructed from the scanned document images, preprocessing steps such as removal of non-text regions, skew-correction, noise removal and binarization is necessary. In the proposed model, text portion of the document image was separated from the non-text region manually. Skew detection and correction was performed using the existing technique proposed by Shivakumar [22]. Binarization can be described as the process of converting a gray-scale image into one, which contains only two distinct tones, that is black and white. In this work, a global thresholding approach 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. It is necessary to thin the document image as the texts may be printed in varying thickness. In this paper, the thinning process is achieved by using the morphological operations. It should be noted that the text block might contain lines with different font sizes and variable spaces between lines, words and characters. Numerals may also appear in the text. It is not necessary to homogenize these parameters. However, it is essential only to ensure that at least 40% of the text block region contains text.

5. The proposed Model

The proposed model is inspired by a simple observation that every language script defines a finite set of text patterns, each having a distinct visual appearance [13]. Scripts are made up of different shaped patterns to produce different character sets. Individual text patterns of one script are collected together to form meaningful text information in the form of a text word, a text line or a paragraph. The collection of the text patterns of the one script exhibits distinct visual appearance. A uniform block of texts, regardless of the content, may be considered as distinct texture patterns (a block of text as single entity) [13]. This observation implies that one may devise a suitable texture classification algorithm to perform identification of text language. In the proposed model, the texture-based features are extracted from the sub bands of wavelet packet transforms.

5.1 Feature Extraction

In this work, the known input images are decomposed through the Wavelet Packet Decomposition using the Haar (Daubechies 1) basis function to get the four sub band images namely Approximation (A) and three detail coefficients - Horizintal (H), Vertical (V) and the Diagonal (D). The Haar wavelet transformation is chosen because the resulting wavelet bands are strongly correlated with the orientation elements in the GLCM computation. The second reason is that the total pixel entries for Haar wavelet transform are always minimum. Through experimentation the Haar basis function up to the level two is found to be best, yielding distinct features and hence Haar basis function up to level two is used in this method. This result in a total of 20 sub bands, four sub bands at the first level and sixteen sub bands (four for each sub band) in the next level as shown in Figure 3.

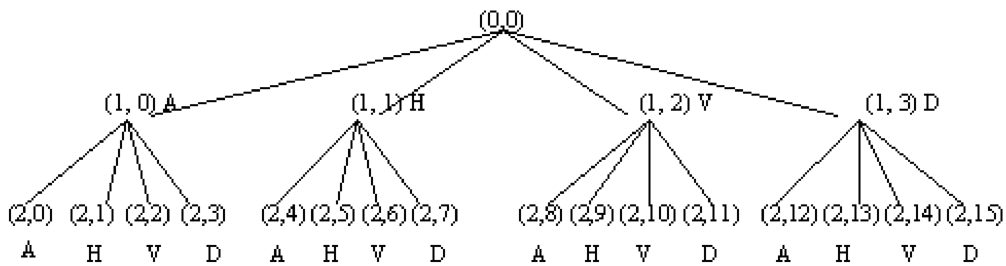


Figure 3. Wavelet Packet Tree up to Level - 2. (A–Approximation, H–Horizontal, V–Vertical and D–Diagonal)

It is not necessary to consider all the twenty sub bands for feature extraction. This is because, the four types of sub bands – approximation, horizontal, vertical and diagonal obtained from the wavelet transforms retain specific type of information by filtering out other information. Therefore, when the horizontal, vertical and diagonal sub bands are decomposed further into four bands, all the four sub bands may not be necessarily used as some information in the second level is lost. So, it is necessary to consider only the relevant sub bands at the second level. For example, in the sub band (1, 1) of level one which gives only horizontal detail coefficients, it is sufficient to consider only the approximation and horizontal detail coefficients of its second level. The vertical and diagonal sub bands of (1, 1) are not considered as they exhibit less or poor information. Thus, the sub bands that exhibit the similar type of coefficients from the two levels are selected. In the proposed method, the sub bands of the two levels are combined to form four groups as given below.

Group 1: Approximation sub bands: (1, 0), (2, 0) = (A, AA)
Group 2: Horizontal sub bands: (1, 1), (2, 1), (2, 4), (2, 5) = (H, AH, HA, HH)
Group 3: Vertical sub bands: (1, 2), (2, 2), (2, 8), (2, 10) = (V, AV, VA, VV)
Group 4: Diagonal sub bands: (1, 3), (2, 3), (2, 12), (2, 15) = (D, AD, DA, DD)

Thus, only fourteen sub bands - two approximate sub band, four horizontal sub band, four vertical sub bands and four diagonal sub bands are selected out of the twenty sub bands.

Many researchers have used the coefficient values of the approximate and detail sub band images as a texture feature vector [12]. According to Andrew Busch [14], a better representation of natural textured images can be obtained by applying a nonlinear function to the coefficients of the wavelet transform. In this paper, the nonlinear transform function proposed by Andrew Busch [14] is applied on the wavelet packet coefficients. So, the wavelet packet coefficients are quantized using the quantization function derived by Andrew Busch [14]. Then, gray level co-occurrence matrices are constructed for the quantized wavelet sub bands. The description of the gray level co-occurrence matrix is briefed out in the next section.

5.1.1. Gray Level Co-occurrence Matrices (GLCMs)

Gray Level Co-occurrence Matrix (GLCM) has been proven to be a very powerful tool for texture image segmentation. Gray-level co-occurrence matrices (GLCMs) are used to represent the pair wise joint statistics of the pixels of an image and have been used for many years as a means of characterizing texture [14]. GLCM is a two dimensional measure of texture, which show how often each gray occurs at a pixel located at a fixed geometric position relative to each other pixel, as a function of its gray level. GLCMs are in general very expensive to compute due to the requirement that the size of each matrix is NxN, where N is the number of gray levels in the image. So, it is necessary to reduce the number of discrete gray levels of the input image in order to obtain co-occurrence matrix of smaller size. So, if the gray levels are divided into fewer ranges, the size of the matrix would be reduced, thus leading to less noisy entries in the matrix.

In this paper, the gray levels of the quantized sub bands are divided into fewer ranges to obtain a new transformed sub band, which results in reduced size of the co-occurrence matrix. Then, from the new transformed sub bands, GLCMs are constructed using the values d=1, where d represents the linear distance in pixels. The value of θ is fixed based on the type of the sub band. For the approximate sub bands i.e., group1 ((1, 0), (2, 0)), GLCMs are constructed with the value $\theta = \{0^0, 45^0, 90^0, 135^0\}$. The value of θ is taken as 0^0 for horizontal sub bands (group2), 90^0 for vertical sub bands (group3) and, 45^0 and 135^0 for diagonal sub bands (group4). Thus, totally, twenty four GLCM (eight GLCM for group1, four GLCM for group2, four GLCM for group3 and eight GLCM for group4) are constructed.

Haralick [24] has proposed the textural features that can be extracted from the co-occurrence matrix. In this paper, Haralick texture features [24] such as inertia, total energy, entropy, contrast, local homogeneity, cluster shade, cluster prominence, and information measure of correlation are extracted from the gray level co-occurrence matrices obtained from the coefficients of the sub bands. These texture features are given in Table 1. These features are known as the wavelet packet co-occurrence features.

Table 1. Wavelet Packet Co-occurrence Features Extracted from a Co-occurrence Matrix C(i, j).

Inertia: $$F1 = \sum_{i,j=0}^{n} (i-j)^2 C(i,j)$$

Total Energy: $$F2 = \sum_{i,j=0}^{n} C^2(i,j)$$

Entropy: $$F3 = -\sum_{i,j=0}^{n} C(i,j) \log C(i,j)$$

Contrast: $$F4 = -\sum_{i,j=0}^{n} C(i,j)|i-j|^k, k \in Z$$

Local Homogeneity: $$F5 = \sum_{i,j=0}^{n} \frac{1}{1+(i-j)^2} C(i,j)$$

Cluster Shade: $$F6 = \sum_{i,j=0}^{n} \left(i - M_x + j - M_y\right)^3 C(i,j)$$

Cluster Prominence: $$F7 = \sum_{i,j=0}^{n} \left(i - M_x + j - M_y\right)^4 C(i,j)$$

Information Measure of Correlation: $$F8 = \frac{-\sum_{i,j=0}^{n} C(i,j) \log C(i,j) - H_{x,y}}{\max\left(H_x, H_y\right)}$$

where $$M_x = \sum_{i,j=0}^{n} iC(i,j) \qquad M_y = \sum_{i,j=0}^{n} jC(i,j)$$

and

$$H_{x,y} = -\sum_{i,j=0}^{n} C(i,j) \log\left(\sum_{j=0}^{n} C(i,j) . \sum_{i=0}^{n} C(i,j)\right)$$

$$H_x = -\sum_{i=0}^{n} \left\{\sum_{j=0}^{n} P(i,j) . \log \sum_{j=0}^{n} P(i,j)\right\}$$

$$H_y = -\sum_{j=0}^{n} \left\{\sum_{i=0}^{n} P(i,j) . \log \sum_{i=0}^{n} P(i,j)\right\}$$

The eight Haralick texture features are extracted from the twenty four GLCMs resulting in a total of 192 features. In order to reduce the dimension of the features, the mean values of the eight features are computed individually from the GLCMs constructed for each of the fourteen sub bands of the four groups. Hence, eight features of any sub band is obtained by taking the average of the each features computed from each GLCMs of that sub band. For example, we have constructed four GLCMs for the sub band (1, 0), eight features are computed from these four GLCMs and the average of each feature is computed from the four GLCMs of the sub band (1, 0). Thus, eight features of the sub band (1, 0) and eight features of sub band (2, 0) of group-1, results in 16 texture features. Similarly, eight features from each sub band of group-2 results in 32 texture features; eight features from each sub band of group-3 results in 32 texture features and eight features from each sub band of group-4 results in 16 texture features. Totally, 112 texture features are computed from the GLCMs constructed for the fourteen sub bands of the wavelet packet transforms and hence, these 112 features are called the wavelet packet co-occurrence features. Thus, the dimensionality of the features has been reduced from 192 to 112 features. As the features are extracted from the two levels of wavelet packet transforms and then the average of the feature values are computed, they could be considered as optimal features. The values of these optimal features show their discriminating strength in classifying the seven script classes considered in this model. Thus, the optimal features are obtained from a training data set of 300 images from each of the seven South Indian scripts - Kannada, Tamil, Telugu, Malayalam, Urdu, Hindi and English. These features are stored in a feature library and used as texture features later in the testing stage.

5.2 Classification

In the proposed model, K -nearest neighbor classifier is used to classify the test samples. The features are extracted from the test image X using the proposed feature extraction algorithm and then compared with corresponding feature values stored in the feature library using the Euclidean distance formula given in equation (3),

$$D(M) = \sqrt{\sum_{j=1}^{N} [f_j(x) - f_j(M)]^2} \tag{3}$$

where N is the number of features in the feature vector f, $f_j(x)$ represents the j^{th} feature of the test sample X and $f_j(M)$ represents the j^{th} feature of M^{th} class in the feature library. Then, the test sample X is classified using the k-nearest neighbor (K-NN) classifier. In the K -NN classifier, a test sample is classified by a majority vote of its k neighbors, where k is a positive integer, typically small. If K =1, then the sample is just assigned the class of its nearest neighbor. It is better to choose K to be an odd number to avoid tied votes. So, in this method, the K -nearest neighbors are determined and the test image is classified as the language type of the majority of these K-nearest neighbors. The experiment is conducted for varying number of neighbors like K = 3, 5 and 7. The performance of classification was best when the value of K = 3.

6. Experimental Results

The proposed algorithm is tested on two sets of database, one constructed manually with 2100 images and the other constructed from the scanned document images of size 1400. The size of the test images was 600x600 pixels. Elaborate experimentation has been conducted on the images with varying coverage of text. The results of the experiments are given in Table 2. The average classification accuracy of the proposed wavelet based method from both the dataset is 99.68% for full text coverage and 98.62% for partial text coverage. From Table 2, it could be seen that 100% accuracy is obtained for Hindi language for both scanned and manually constructed dataset and also for images covered with 50% texts. The experimental results demonstrate the effectiveness of the proposed texture features. The proposed algorithm was implemented using MATLAB R2007b. The average time taken to identify the script type of the document was 0.2843 seconds on a Pentium-IV with 1024 MB RAM based machine running at 1.60 GHz.

Table 2. Percentage of Recognition of Kannada, Tamil, Telugu, Malayalam, Urdu, Hindi and English scripts.

Script Type	Scanned Dataset		Manually Created Dataset	
	50% text present	Full text covered	50% text present	Full text covered
Kannada	98.6	99.8	98.8	99.8
Malayalam	97.8	99.4	98.2	99.6
Tamil	98.7	99.6	98.4	99.7
Telugu	97.6	99.3	98.8	99.5
Urdu	98.7	99.8	98.4	100
Hindi	100	100	100	100
English	98.2	99.5	98.6	99.6
Average	**98.51**	**99.63**	**98.74**	**99.74**

7. Conclusion

In this paper, a new texture-based global approach is presented which can identify seven scripts using a new set of texture features. The texture features are extracted from the GLCMs constructed from a set of wavelet packet sub band coefficients. All the features are extracted globally from a given text block which does not require any complex and reliable segmentation of the document image into lines and characters. The experimental results demonstrate that the new approach is efficient and can be used for many practical applications, which require processing large volumes of data. Thus, the proposed global approach of script identification in a document image facilitates many important applications such as separating a huge collection of documents printed in different scripts for further processing like selecting the script specific OCR system in a multilingual environment.

Another application of the proposed method is that the method can be extended to identify and separate more number of script classes as the script independent features are used. Hence, the proposed global approach has the potential to become a generalized approach for script identification.

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