

Haralick Texture Features based Syriac(Assyrian) and English or Arabic documents Classification

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Abstract: Script identification is very essential before running an individual OCR system. Automatic language script identification from document images facilitates many important applications such as sorting, transcription of multilingual documents and indexing of large collection of such images, or as a precursor to optical character recognition (OCR), in this paper the characterized between Syriac and English documents or between Syriac and Arabic documents were the characterized by extracting Haralick texture Features. it is investigated a texture as a tool for determining the script of document image, based on the observation that text has a distinct visual texture. Further, K nearest neighbour algorithm is used to classify 300 text blocks into one of the two scripts: Syriac, and English, or Syriac and Arabic based on Haralick texture Features. The script was inserted to the System with different rotation angles between 0° and 135° and the results of recognition were good.

Keywords: Syriac script; Haralick Texture Features; OCR; English script; Arabic script; knn algorithm.

1. INTRODUCTION

Script and language identification are a key part of automatic processing of document images in an international environment. A document's script must be recognized in order to choose an appropriate optical character recognition (OCR) algorithm. For scripts used by more than one language, discriminating the language of a document prior to OCR is also helpful, and language identification is crucial for further processing steps such as routing, indexing, or translation.

One of the important tasks in machine learning is the electronic reading of documents. All documents can be converted to electronic form using a high performance Optical Character Recognizer (OCR). Recognition of bilingual documents can be approached by the recognition via script identification.

This paper considers the discrimination between the Syriac and English scripts and between the Syriac and Arabic scripts according to an analysis of text block.

The Syriac (Assyrian) language is one of the Semitic languages that is being spoken in Iraq, Syria, Turkey and Iran by Assyrians. It's an ancient language, one of the rarest and oldest in the world.

Syriac is an ancient Iraqi language, and it is culturally used by human beings in Iraq. It has many religious scripts as well as scientific and literary books which have been completed and achieved throughout the long history and efficient civilization for this language, and conveying this important thought for communication between the present and past generations.

Over the past decades, many different researches and papers have been concerned to discriminate between the two or more difference languages for example Arabic and English or between Indian and English documents and ect., but no research has been achieved towards the discriminating between Syriac and other languages.

This paper presents a scheme for identification between Syriac and English scripts or between Syriac and Arabic script based on Haralick Texture Features.

Two scripts were classified by the classification algorithm, these scripts are Syriac and Roman (English) or Syriac and Arabic. Classification accuracy depends on the rotation angle of the script.

2. RELATED WORK

Santanu Choudhuri, et al. [1] has proposed a method for identification of Indian languages by combining Gabor filter based technique and direction distance histogram classifier considering Hindi, English, Malayalam, Bengali, Telugu and Urdu. Dhanya et al. [2] have used Linear Support Vector Machine (LSVM), K-Nearest Neighbour (K-NN) and Neural Network (NN) classifiers on Gabor-based and zoning features to classify Tamil and English scripts. Wood et al. [3] have proposed projection profile method to determine Roman, Russian, Arabic, Korean and Chinese characters.

Later, script recognizer[4] has been extended to four scripts/ languages (Kannada, Hindi, English and Urdu) with different font sizes and styles by relaxing their constraints over different font sizes[5].

Horizontal projection was attempted [6] to separate two languages English and Arabic at text line level. Here, the horizontal projection profiles of Arabic text have a single peak corresponding to the baseline of the Arabic writing, where characters are connected together. In contrast, projections of English text have two major peaks corresponding to x-line and baseline. The projections of Arabic text lines are smooth while the projections of English text line have sharp jumps. Multichannel Gabor filtering designed with four frequencies and four orientations was also applied over the bilingual document images[7]. Arabic-English, Chinese-English, Hindi-English and Korean-English bilingual dictionaries to identify the script at word level.

Using the combination of shape, statistical and Water Reservoirs, an automatic line-wise script identification scheme from printed documents containing five most popular

scripts in the world, namely Roman, Chinese, Arabic, Devnagari and Bangla has been introduced[8].

3. PROPOSED APPROACH

The paper primarily aims for block level classification; blocks of text are first extracted from the scanned document. For block of text extracted, Haralick Texture features are computed. These features are integrated to form database of vectors which are then used for Syriac and English or Arabic text separation via k-NN classifier. For better understanding, Figure.1 shows a schematic work-flow of the system



Figure. 1 A screen-shot of an overall work-flow of the system

3.1 Preprocessing

The preliminary task is to do pre-processing. Pre-processing techniques are application dependent. In this paper initially, 600 x600 text blocks are segmented manually from the document images of Syriac, English and Arabic and created 300 text blocks. Out of these 300 images Syriac, English, and Arabic are 100 each. A sample images text blocks of Syriac , English and Arabic are shown in figure 2.



(a)

Responses in question three concerned the importance of rainforests. The dual main idea, raised by 64% of the pupils, was that rainforests provide animals with lush habitats. Fewer students reported that rainforests provide plant habitats, and even fewer mentioned the indigenous populations of rainforests. More girls (70%) than boys (6%) named the idea of rainforests as animal habitats.

Similarly, but at a lower level, more girls (13%) than boys (5%) said that rainforests provided human habitats. These observations are generally consistent with our previous studies of pupils' views about the use and conservation of rainforests. In which girls were shown to be more sympathetic to animals and expressed views which seem to place an intrinsic value on non-human animal life.

The fourth question concerned the causes of the destruction of rainforests. Perhaps encouragingly, more than half the pupils (59%) identified that it is human activities which are destroying rainforests, some pinpointing the responsibility by the use of terms such as 'we cut'. About 18% of the pupils referred specifically to logging activity.

One misconception, expressed by some 10% of the pupils, was that acid rain is responsible for rainforest destruction; a similar proportion said that pollution is destroying rainforests. Here, children are reflecting rainforest destruction with damage to the forests of Western Europe by these forces. While two thirds of the pupils provided the information that the rainforests provide oxygen, in some cases this response also embraced the misconception that rainforest destruction would reduce atmospheric oxygen, making the atmosphere incompatible with human life on Earth.

In answer to the final question about the importance of rainforest conservation, the majority of children simply said that we need rainforests to survive. Only a few of the pupils (6%) mentioned that rainforest destruction may contribute to global warming. This is surprising considering the high level of media coverage on this issue. Some children expressed the idea that the conservation of rainforests is not important.

The results of this study suggest that certain ideas permeate in the thinking of children about rainforests. Pupils' responses indicate some misconceptions in basic scientific knowledge of rainforests' ecosystems such as their ideas about rainforests as habitats for animals, plants and humans and the relationship between climate change

(b)



(c)

Figure. 2 Examples of document images used for training and testing.

(a) Syriac, (b) English, and (c) Arabic.

3.2 Haralick TEXTURE Features EXTRACTION

From each block of normalized text, the Haralick texture features are evaluated for the purpose of script identification. Haralick Texture features are first reported in [9] for image classification. For better understanding, texture can also be defined as: it is property which contains important information about structural arrangement of surfaces and their relationship with surrounding environment. In this paper, the Haralick Texture of each test image is extracted as attributes to build a database which is used at classification stage. These set of statistical texture features collectively used to generate a feature vector.

Haralick features are used for analyzing the texture of an image on the other hand; Haralick features offer 13 different elements that define the textural structure of an image. Haralick features can be defined as follows [9].

Contrast, Homogeneity, Dissimilarity, Energy and Entropy, as Angular second moment:

$$f_1 = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} \{p(i, j)\}^2$$

Contrast:

$$f_2 = \sum_{n=0}^{N_g-1} n^2 \left(\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p(i, j) \right) \text{ when } |i - j| = n$$

Correlation:

$$f_3 = \frac{\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} (ij)p(i, j) - \mu_x \mu_y}{\sigma_x \sigma_y}$$

Sum of squares: Variance

$$f_4 = \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} (i - \mu)^2 p(i, j)$$

Inverse Difference Moment homogeneity
 Homogeneity (HOM) (also called the "Inverse Difference Moment")

$$f_5 = \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} \frac{1}{1 + (i - j)^2} p(i, j)$$

Sum Average

$$f_6 = \sum_{i=2}^{2Ng} i p_{x+y}(i)$$

Sum Variance

$$f_7 = \sum_{i=2}^{2Ng} (i - f_6)^2 p_{x+y}(i)$$

Sum Entropy

$$f_8 = - \sum_{i=2}^{2Ng} p_x + y^{(i)} \log\{p_x + y^{(i)}\}$$

Entropy

$$f_9 = - \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} p(i, j) \log(p(i, j))$$

Difference Variance

$$f_{10} = E[p_x - y^2] - E[p_x - y]^2$$

Difference Entropy

$$f_{11} = - \sum_{i=0}^{Ng-1} p_{x-y^{(i)}} \log\{p_{x-y^{(i)}}\}$$

Information Measures of Correlation

$$f_{12} = \frac{HXY - HXY1}{\max\{HX, HY\}}$$

$$f_{13} = (1 - \exp[-2.0(HXY2 - HXY)])^{1/2}$$

3.3 Classification

The traditional and simplest classification algorithm is k-nearest neighbour algorithm (k-NN). It is a method of classifying the instances based on the nearest training examples in the feature space. It classifies an object based on a majority vote of its neighbours, with the object being assigned to the class most common amongst its k nearest neighbours. The training set includes the data for classification for each specific.

For every new input, the Haralick textural features are obtained. A sample of Haralick textural features of Syriac, English and Arabic scripts of figure 2 are represented in Table 1.

The following are the steps of the algorithm

1. Given an input image X with different rotation angles between 0° and 135°, determine its distance measure based on the computation of textural features.
2. Determine the k (k=3) nearest neighbor in the training set which comprises of the Haralick features.
3. Assign the image X to the closest match.

Table1: The sample Haralick Texture Features of Syriac, English and Arabic Scripts

script Features	Syriac	English	Arabic
F1	0.6343	0.3782	0.5194
F2	0.2930	0.7979	0.2831
F3	175.4046	246.0818	221.0589
F4	14.2433	14.4900	16.3956
F5	0.9252	0.7981	0.8971
F6	7.4427	7.4751	8.0417
F7	45.6203	40.2149	50.4000
F8	0.8193	1.2732	1.0232
F9	1.0219	1.7562	1.2327
F10	0.0935	0.0547	0.0801
F11	0.4700	0.8992	0.5703
F12	-0.4320	-0.1738	-0.2773
F13	0.6561	0.5331	0.5725

4. DISCUSSION

Experimentations are carried out with KNN classifier. To evaluate the a sample image of size 600x600 pixels is selected manually from each document image and created 300 text block images. Out of these 300 images Syriac, English, and Arabic are 100 each. The accuracy of the classification achieved for script identification is shown in Tables 2 and 3.

The achieved results of the classification depend on the rotation angle of script.

Table 2. Text block Syriac-English scripts identification results

Type of Documents	No. of documents	Classified correctly	% correct classification
Syriac –English			
Syriac – with rotation 0°	100	100	100%
Syriac – with rotation 45°	100	100	100%
Syriac – with rotation 90°	100	100	100%
Syriac – with rotation 135°	100	100	100%
English – with rotation 0°	100	75	75%
English – with rotation 45°	100	0	0%
English – with rotation 90°	100	75	75%
English – with rotation 135°	100	0	0%

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Table 3. Text block Syriac-Arabic scripts identification results

Type of Documents	No. of documents	Classified correctly	% correct classification
Syriac –Arabic			
Syriac – with rotation 0°	100	100	100%
Syriac – with rotation 45°	100	100	100%
Syriac – with rotation 90°	100	100	100%
Syriac – with rotation 135°	100	100	100%
Arabic– with rotation 0°	100	100	100%
Arabic– with rotation 45°	100	0	0%
Arabic– with rotation 90°	100	100	100%
Arabic– with rotation 135°	100	0	0%

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