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Text-independent writer recognition using multi-script handwritten texts

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ABSTRACT

This paper presents a text-independent writer recognition method in a multi-script environment. Handwritten texts in Greek and English are considered in this study. The objective is to recognize the writer of a handwritten text in one script from the samples of the same writer in another script and hence validate the hypothesis that writing style of an individual remains constant across different scripts. Another interesting aspect of our study is the use of short handwritten texts which was implied to resemble the real life scenarios where the forensic experts, in general, find only short pieces of texts to identify a given writer. The proposed method is based on a set of run-length features which are compared with the well-known state-of-the-art features. Classification is carried out using *K*-Nearest Neighbors (*K*-NN) and Support Vector Machines (SVM). The experimental results obtained on a database of 126 writers with 4 samples per writer show that the proposed scheme achieves interesting performances on writer identification and verification in a multi-script environment.

1. Introduction

Handwriting based writer recognition offers a number of useful applications which make it an attractive and promising research area in pattern recognition (Schlapbach and Bunke, 2006). The classification task in pattern recognition comprises assigning a questioned pattern to one of the classes among a set of known classes. In case of writer recognition, the pattern comprises a handwritten sample while each writer constitutes a class, the task being to assign the sample in question to one of the (writer) classes.

Writer recognition is the process of automatically recognizing who has written a given text based on an individual's writing preferences and characteristics which are reflected in his/her handwriting. Writer recognition comprises two different tasks: writer identification and writer verification. Writer identification determines which writer, amongst a set of known writers, has written a given sample. Writer verification is the task of finding out whether two handwritten documents are written by the same person or not. In other words, writer identification is a one-to-many while writer verification is a one-to-one problem.

Writer recognition approaches are traditionally categorized into two distinct families: text-dependent and text-independent approaches. In text-dependent approaches, each writer must provide exactly the same text for training and test samples. Text-independent writer recognition on the other hand identifies or verifies the writer without any constraints on the textual content of the samples being compared.

Writer recognition systems offer a number of applications mainly including biometric recognition (Bulacu and Schomaker, 2007; Djeddi and Souici-Meslati, 2010, 2011), personalized handwriting recognition (Nosary et al., 2004), automatic forensic document examination (Van et al., 2005; Schomaker et al., 2007), classification of ancient manuscripts (Schomaker et al., 2007; Siddiqi et al., 2009) and smart meeting rooms (Liwicki et al., 2006). These applications have resulted in a renewed research interest in this area over the last few years.

Notable advancements in writer recognition in the recent years have resulted in new research directions. These include introduction of new features (Bulacu and Schomaker, 2007; Siddiqi et al., 2009), combining different types of features (Bulacu and Schomaker, 2007; Djeddi and Souici-Meslati, 2010), studying the sensitivity of character size on writer identification (Ozaki et al., 2006) and investigating writer identification in multi-script environments (Garain and Paquet, 2009). An interesting study is the impact of ruling lines on writer identification (Chen et al., 2010) which was followed by using model perturbed handwriting for writer identification (Chen et al., 2011). Combination of online and offline writings (Chaabouni et al., 2011) has also been effective in characterizing the writer. Writer identification task has also been extended to a novel scenario called writer retrieval (Atanasiu

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et al., 2011) which involves the retrieval, from a set of documents, all those produced by the same writer. Other significant contributions include identifying the author of handwritten music scores (Fornes et al., 2008), using immunological models in the writer identification task (Djeddi and Souici-Meslati, 2011) and reducing the search space for a writer identification system by integrating a retrieval mechanism (Djeddi et al., 2012a). In an attempt to objectively compare the performance of different writer recognition systems, five competitions on this subject were also organized in conjunction with the International Conference on Document Analysis and Recognition (ICDAR 2011) and the International Conference on Frontiers in Handwriting Recognition (ICFHR 2012) by research teams from Qatar (Hassaine et al., 2011; Hassaine and Al-Maadeed, 2012), Spain (Fornes et al., 2011) and Greece (Louloudis et al., 2011, 2012).

Writer recognition in monolingual handwritten texts is a mature area of study. A large number of scripts have been considered in the literature including Chinese (Wang and Ding, 2004), Japanese (Kameya et al., 2006), Arabic (Bulacu et al., 2007; Djeddi and Souici-Meslati, 2010, 2011), Bengali (Chanda et al., 2010), Telugu (Purkait et al., 2010), Oriya (Chanda et al., 2012) and Latin (Bulacu and Schomaker, 2007; Nosary et al., 2004; Schomaker et al., 2007; Bensefia et al., 2005; Kameya et al., 2006; Siddiqi and Vincent, 2010). Writer recognition in a multi-script environment, however, remains a relatively unexplored area with only one contribution (Garain and Paquet, 2009) to the best of authors' knowledge.

The writer identification scheme proposed in (Garain and Paquet, 2009) was evaluated by mixing the handwritten images from the RIMES database (Grosicki et al., 2008) (containing French handwritten texts from 382 writers) with those from the ISI database (comprising Bengali handwritten texts from 40 different writers). The two datasets however have no common writers and their proposed method does not focus on studying whether an individual writing more than one script (for examples someone who writes Bengali & French) share some common characteristics across different scripts. Hence, all the existing writer recognition systems are restricted in recognizing the writer from handwritten documents written in only one language.

The first objective of this study is to extend the research in writer recognition to a true multi-script environment by studying and validating the idea of recognizing the writer of a given text written in one script from the samples of the same writer written in another script. In order to develop such multi-script writer recognition systems, it is necessary to use script independent features. Features based on allographs have been very effective for writer recognition with text samples in one script only. Allographs, however, are very much linked with the script under study and therefore do not seem to be an attractive choice in a multi-script environment. We believe that the use of global features such as those based on texture can be very useful as these features are more linked to the writing style of the writer rather than the script under study. Our proposed method is based on run-length features (Galloway, 1975; Djeddi and Souici-Meslati, 2010) which provide an effective way to characterize the writers of documents written in different scripts. The performance of these features is also compared with a number of recent writer identification methods (Bulacu and Schomaker, 2007; Siddiqi and Vincent, 2010; Garain and Paquet, 2009).

The second objective of our study is to investigate writer recognition on short handwritten texts. In traditional writer recognition systems, a large amount of writing is required to characterize and recognize correctly the writer of a given text sample. The performance of these systems on small amounts of text is likely to degrade significantly. For practical problems, especially forensic examination, the amount of available text is generally very limited. In such scenarios, the state-of-the-art writer recognition systems evaluated on larger amounts of text may not produce acceptable results when limited amounts of text are available. Writer recognition from short handwritten texts therefore presents an interesting area of study.

The rest of this paper is organized as follows: Section 2 gives a brief description of the database used for carrying out the experimental evaluations. Section 3 describes the proposed features and the way they are extracted. We then present the used classifiers followed by the detailed results and an analysis of the experimental evaluations. We finally conclude the paper with some discussion on future research directions on the subject.

2. Database

In our study, we employed the database of the Competition on Writer Identification – Challenge 1: Latin/Greek Documents (Louloudis et al., 2012). The database was developed by a research team at the Institute of Informatics and Telecommunications in the National Center for Scientific Research "Demokritos", Greece. The database comprises samples from 126 Greek writers; each contributed four pages, two in Greek and two in English. The handwritten paragraphs were scanned and binarized and did not include any non-text elements. The Greek documents correspond to the native language of the writers.

After having presented the database, we summarize the similarities and differences between Greek and English. This will help support the argument that the proposed method is independent of the script under study.

Comparing Greek and English texts (Fig. 1(a)), it can be seen that there are some similarities between the two. Both English and Greek are read and written from left to right, have capital and small letters (Fig. 1(b)), have spaces between the words (Fig. 1(a)) and share some common upper case letters (Fig. 1(b)). Despite these similarities, there are some significant differences between the two. Greek alphabet is only used to write Greek whereas the Latin alphabet is used to write a large number of languages, English being one of the examples. Most of the letters have completely different shapes across the two scripts. Many of the capitals letters of the English alphabet look like their "printed" small letters which is not the case in Greek (Fig. 1(b)). English alphabet comprises twenty-six capital and twenty-six small letters, but, the Greek alphabet has twenty-four capital letters and twenty-five small letters (Fig. 1(b)). While all English letters retain their original shapes, one Greek letter takes a different form when it appears at the end of a word. Finally, accent marks or diacritics are rare in English but are a common occurrence in Greek (Fig. 1(a)).

3. Feature extraction

The proposed method is mainly based on a set of features extracted from Grey Level Run Length (GLRL) matrices (Galloway, 1975; Djeddi and Souici-Meslati, 2010). We have also implemented some of the latest state-of-the-art methods that have shown good results on monolingual writer recognition.

3.1. Run-length features

We characterize the writing style of a writer by computing the probability distribution of run-length features. These features are determined on a binary image of handwriting where the black pixels correspond to the ink trace and the white pixels correspond to the background. The run-lengths are computed on the complete image directly and do not require any segmentation of text into words or characters. For calculation of run-lengths, the image is

Όλοι οι άνθρωποι γεννιούνται ελεύθεροι και ίσοι στην αξιοπρέπεια και τα δικαιώματα. Είναι προικισμένοι με λογική και συνείδηση, και οφείλουν να συμπεριφέρονται μεταξύ τους με πνεύμα αδελφοσύνης
All human beings are born free and equal in dignity and rights. They are endowed with reason and conscience and should act towards one another in a spirit of brotherhood

(a)

Greek small letters	α β γ δ ε ζ η θ ι κ λ μ ν ξ ο π ρ σ ς τ υ φ χ ψ ω
Greek capital letters	Α Β Γ Δ Ε Ζ Η Θ Ι Κ Λ Μ Ν Ξ Ο Π Ρ Σ Τ Υ Φ Χ Ψ Ω
English small letters	a b c d e f g h I j k l m n o p q r s t u v w x y z
English capital letters	A B C D E F G H I J K L M N O P Q R S T U V W X Y Z

(b)

Fig. 1. Greek against English text: (a) the same paragraph written in Greek and English (b) small and capital letters of Greek and English.

scanned in four principle directions: horizontal, vertical, left-diagonal and right-diagonal. The normalized histogram of these run-lengths is interpreted as a probability distribution characterizing the writer. The method considers horizontal, vertical, left-diagonal and right-diagonal run-lengths of white extracted from the original image while the horizontal, vertical, left-diagonal and right-diagonal run-lengths of black extracted from the image after applying Sobel edge detection where only the edge pixels are "*on*".

We start with defining a '*run*' as a sequence of connected pixels which have the same color along a given direction. If A_iA_j is a run composed of pixels $A_i, A_{i+1}, \ldots, A_{j-1}, A_j$ with an identical color, pixel A_{i-1} must differ in color from pixel A_i, while pixel A_j must differ from pixel A_{j+1}. We next define a run-length matrix P as follows: each element $P(i,j)$ represents the number of runs with pixels of color i and length of run j along a specific direction. The size of the matrix P is N by K, where N is the number of colors in the image and K is equal to the maximum possible run-length in the corresponding image.

A direction is defined using a displacement vector $d(x,y)$, where x and y are the displacements for the x and y-*axis* respectively. The four principal directions that we consider are: right-diagonal (45°), vertical (90°), left-diagonal (135°) and horizontal (180°). Calculating the run-length encoding for each direction produces a total of four run-length matrices.

The proposed feature extraction method is illustrated by an example in Fig. 2. We consider an 8×6 image with two colors $C = \{0,1\}$. This image represents the digit '*2*'.

Each element of the matrix specifies the number of times the image contains runs of length $\{1,2,3,4,5,6\}$ in the directions 45°, 135° and 180° and runs of length $\{1,2,3,4,5,6,7,8\}$ in the 90° direction. The first element of the first row of the matrix is the number of times color 0 appears in isolation, the second element is the number of times it appears in pairs and so on. The subsequent row captures the same information for color 1 in the image.

The four run-length matrices are converted into (normalized) vectors which are then concatenated to obtain a single vector characterizing the writer of a document. This naturally leads to the problem of the large dimensionality of the feature vector. However, it can be noticed that most of the non-zero values are in the first few columns of the matrix. We therefore keep only a sub-set of columns (chosen empirically) for each of the matrices. For run-lengths on black pixels, we keep the first 100 columns for each of the four directions whereas for white pixels we keep the first 50 columns. This gives a total of 600 features $(100 \times 4 + 50 \times 4)$ for each writing.

These run-length features are similar to those we employed in the system that participated in the ICDAR2011 Writer Identification Contest (Louloudis et al., 2011). A part of these features were

0	1	1	1	1	0
1	0	0	0	0	1
1	0	0	0	0	1
0	0	0	0	1	0
0	0	0	1	0	0
0	0	1	0	0	0
0	1	0	0	0	1
1	1	1	1	1	1

(a)

2	1	2	2	1	1
9	2	0	0	0	1

(b)

3	2	3	2	1	0	0	0
11	4	0	0	0	0	0	0

(c)

7	3	2	1	0	1
15	2	0	0	0	0

(d)

4	2	3	3	0	0
9	0	0	1	0	1

(e)

Fig. 2. Calculation of run-length matrices (a) an 8×6 image with two color values (0 and 1) (b) run-length matrix for 45° (c) run-length matrix for 90° (d) run-length matrix for 135° (e) run-length matrix for 180°.

also used in the ICDAR2011 Arabic Writer Identification Contest (Hassaine et al., 2011), the ICDAR 2011 Writer Identification on Music Scores Competition (Fornes et al., 2011), the ICFHR2012 Competition on Writer Identification – Challenge 2: Arabic Scripts (Hassaine and Al-Maadeed, 2012) and the ICFHR2012 Competition on Writer Identification Challenge 1: Latin/Greek Documents (Louloudis et al., 2012). The writer identification system based on these features achieved the third best performance in the ICDAR2011 writer identification contest (Louloudis et al., 2011) and the second best results in the competition on writer identification on music scores (Fornes et al., 2011). These results are a good indicative of the effectiveness of these features in characterizing the writers. These features do not use any knowledge about the script of writing and their performance is comparable with that of the method proposed in (Siddiqi and Vincent, 2010) while they outperform the edge-direction features proposed in (Al-Maadeed et al., 2008a), the grapheme features presented in (Al-Maadeed et al.,

Table 1
Overview of the implemented features.

Feature	Description	Dimension
*f*1	Run-length distribution on white pixels in four directions	200
*f*2	Run-length distribution on black pixels in four directions	400
*f*3	Run-length distribution on white and black pixels in four directions	600
*f*4	Edge-direction distribution using 16 angles (Bulacu and Schomaker, 2007)	16
*f*5	Edge-hinge with fragment of length equal to 7 pixels (Bulacu and Schomaker, 2007)	2304
*f*6	Polygon based features (Siddiqi and Vincent, 2010)	42
*f*7	Chain code based global features (Siddiqi and Vincent, 2010)	314
*f*8	Chain code based local features (Siddiqi and Vincent, 2010)	230
*f*9	Codebook based features (Siddiqi and Vincent, 2010)	200
*f*10	AR Coefficients based features (Garain and Paquet, 2009)	24

2008b) and the *K*-adjacent segment (KAS) features discussed in (Jain and Doermann, 2011). The script independence of the proposed features has also been verified on IFN/ENIT Arabic database (Pechwitz et al., 2002) in our previous studies (Djeddi and Souici-Meslati, 2010, 2011; Djeddi et al., 2012a, 2012b).

3.2. State-of-the-art features

In an attempt to study the effectiveness of run-length features in a multi-script environment, the performance of these features is compared with some of the latest state-of-the-art methods that have shown good results on monolingual writer recognition. These include the edge-direction and edge-hinge features proposed in (Bulacu and Schomaker, 2007), a combination of codebook and visual features, extracted from chain code and polygonized representation of contours, presented in (Siddiqi and Vincent, 2010) and the autoregressive (AR) coefficients proposed in (Garain and Paquet, 2009). A detailed description of these features along with the results achieved can be found in the respective papers.

Table 1 summarizes, for each of the used features, the corresponding number, description and the dimension.

4. Writer recognition

Once the handwritings are represented by the set of features, writer identification is performed by using two traditional classifiers: *K*-Nearest Neighbors and Multiclass Support Vector Machines. A brief introduction to these classifiers is given below.

1. *K*-Nearest Neighbors (*K*-NN), a memory-based classification method, is a non-parametric inductive learning algorithm storing the training instances in a memory structure. It can predict the class label of a data point by a majority vote of the *K* nearest neighbors of this data point with ties broken at random. *K* is set to be 1 in our experiments and the distance metric used is Manhattan. The distance of the query document is computed with all the documents in the training base and the retrieved list of writers is sorted in the order of increasing distance from the questioned document. The writer of the query document is identified as writer of the training document reporting the minimum distance.
2. Multiclass Support Vector Machines (SVM) is a learning algorithm typically used for classification problems. The goal of the Support Vector Machines (SVM) is to optimize the ability to correctly classify unseen data. It addresses the problems of many other learning algorithms such as local minima, over fitting and an inconveniently large number of tunable parameters. We have employed the one-against-all SVM implemented using the '*SVM and Kernel Methods Matlab toolbox*' (Canu et al., 2005). The SVM is trained with a Gaussian kernel where the bound on the Lagrangian multipliers 'C' is fixed at 10,000 and the conditioning parameter for QP method lambda is set to 10^{-5}, both parameters chosen empirically. The features extracted from the query document are fed to the SVM trained on the set of writers under study which classifies it as belonging to one of the writers in the training base.

For writer verification, we compute the Manhattan distance between two given documents and consider them to be written by the same person if the distance falls within a predefined decision threshold. Beyond the threshold value, we consider the samples to be written by different writers. By varying the acceptance threshold, the ROC curves are computed and the verification performance is quantified by the Equal-Error-Rate (EER), the point where False Acceptance Rate (FAR) and False Rejection Rate (FRR) are equal. The lower the Equal-Error-Rate (EER), the higher the accuracy of the system.

5. Experimental results and discussion

This section presents the experiments performed to study the effectiveness of the proposed features for writer recognition and to validate the hypothesis that the writing style of an individual remains more or less the same across different scripts. The performance measures used are the Top-1 identification rate and the Equal-Error-Rate (EER) for verification task. Section 5.1 presents the language-dependent evaluations; Section 5.2 discusses the writer recognition results on Greek against English text while the last section presents a study on the stability of the features.

5.1. Language-dependent experiments

In this section, we present and analyze the performance of the proposed features on writer identification and verification using text samples from each language independently. For each of the two languages considered in our study, one image of each of the 126 writers is used for training while the other is used in testing. We considered two different evaluation scenarios. In the first one, we choose the first image of each writer for training and the second image for testing. In the second scenario, we choose the second image for training and the first image for testing. Table 2 presents the identification rates of the two classifiers and the Equal-Error-Rates (EER) on Greek samples using the proposed run-length features as well as the state-of-the-art features presented in Section 3.2. Table 3 presents the same results for writing samples in English.

An analysis of the results presented in Tables 2 and 3 leads to the following observations.

- The combination of run-length features (*f*3) outperforms all other features. It has the best performance in all writer identification experiments and the same trend can be seen on the verification task as well.
- The state-of-the-art methods which have shown very high identification rates on large data sets like IAM (Marti and Bunke, 2002) and RIMES (Grosicki et al., 2008), show a significant drop in performance in our experiments. This is due to the fact that the images in our experiments have small amounts of text. Hence these methods are not very effective when a limited amount of text is available.

Table 2
Writer identification and verification results on Greek text.

Feature	SVM identification rate		KNN identification rate		EER
	Scenario 1 (%)	Scenario 2 (%)	Scenario 1 (%)	Scenario 2 (%)	
*f*1	58.73	61.11	61.11	69.84	8.38
*f*2	81.75	79.36	84.92	82.54	3.63
*f*3	**92.06**	**88.09**	**92.06**	**91.27**	**2.78**
*f*4	48.41	47.62	67.46	61.11	6.76
*f*5	73.81	82.54	82.54	78.57	5.15
*f*6	57.94	55.56	67.46	65.08	5.16
*f*7	64.29	69.84	62.70	60.32	6.73
*f*8	47.62	46.82	58.73	63.49	9.13
*f*9	65.08	67.46	63.49	73.02	9.22
*f*10	61.11	64.29	68.25	65.08	3.97

Table 3
Writer identification and verification results on English text.

Feature	SVM identification rate		KNN identification rate		ERR
	Scenario 1 (%)	Scenario 2 (%)	Scenario 1 (%)	Scenario 2 (%)	
*f*1	49.21	49.21	42.86	46.03	11.90
*f*2	77.78	80.95	76.98	73.81	5.23
*f*3	**83.33**	**87.30**	**80.95**	**82.54**	**3.57**
*f*4	46.03	50.00	62.70	54.76	7.54
*f*5	79.36	80.16	73.02	80.16	4.76
*f*6	59.52	53.17	69.05	65.08	5.62
*f*7	66.67	69.84	59.52	60.32	7.14
*f*8	44.44	50.00	54.76	53.17	7.54
*f*9	71.43	78.57	70.63	76.19	9.07
*f*10	63.49	54.76	68.25	68.25	4.42

- The combination of run-length features (*f*3) achieves reasonably good results on small amounts of text and hence are less sensitive to the amount of text as opposed to other traditional features.
- It can also be noted that the run-lengths on black pixels (*f*2) are more informative as compared to those on white pixels (*f*1). The run-lengths on white pixels alone are not very discriminative but contribute to improve the performance when combined with the run-lengths on black pixels.
- The identification and verification results are better on Greek text as compared to English for all features except the codebook based features. This may be attributed to the fact that these samples were in the native language of the writers. It may be possible that the peculiarities and characteristics of different writers involved in our experiments are reflected better while writing in their native language.
- It can also be observed from Tables 2 and 3 that the codebook features (*f*9) are alphabet-dependent. Since the codebook was generated on a set of English documents, the identification rates decrease from 71.43% and 78.57% (for Scenarios 1 and 2, respectively) on English texts to 65.08% and 73.02% for the two scenarios with Greek documents.

5.2. Greek against english experiments

This section presents the evaluations conducted to test the validity of the hypothesis that writer style remains constant across different scripts. We conducted a series of experiments by using text samples in the training set which are in a different script than those in the test data set. Two different scenarios are considered in our study: in the first one the classifiers are trained on Greek samples and evaluations are carried out on English samples while the opposite is considered in the second scenario. The identification and verification results of these experiments are reported in Table 4.

An analysis of the results presented in Table 4 leads to the following observations:

Table 4
Writer identification and verification results on Greek against English text and vice versa.

Feature	SVM identification rate		KNN identification rate		EER
	Scenario 1 (%)	Scenario 2 (%)	Scenario 1 (%)	Scenario 2 (%)	
*f*1	38.89	42.46	41.27	37.70	14.55
*f*2	60.32	61.11	60.32	62.30	7.80
***f*3**	**73.02**	**76.59**	**73.41**	**76.19**	**5.75**
*f*4	32.54	42.06	38.49	38.49	12.57
*f*5	62.30	57.94	61.51	61.11	8.07
*f*6	30.56	29.76	39.29	38.09	11.77
*f*7	49.21	50.00	32.94	32.54	14.28
*f*8	30.56	34.52	33.33	30.95	14.75
*f*9	55.16	51.98	50.40	44.05	14.35
*f*10	40.08	42.86	39.68	39.68	9.99

- It can be observed that performance of the evaluated features on both identification and verification is less impressive as compared to that obtained on language-dependent experiments. The difference between the performances of these features is also more significant.
- As in case of language-dependent experiments, the run-length features (*f*3) continue to be the best set of features by realizing identification rates of 73.02% and 76.59% (for scenarios 1 and 2, respectively with SVM as classifier) and an Equal-Error-Rate (EER) of 5.75%. Using *K*-NN classifier, the same set of features report identification rates of 73.41% and 76.19% for the two scenarios. Considering that the experiments were carried out in a multi-script environment and the amount of text was also very limited, these results are very promising.
- The AR coefficients (*f*10), that have been evaluated in partially multi-scrip environment (Garain and Paquet, 2009) report identification rates of 40.08% and 42.86% and an equal error rate of about 10%. Hence, they do not seem to be an appropriate choice in a true multi-script scenario.
- It is also interesting to note that most of the state-of-the-art features are more dependent on the script than run-length features. They model only the characters of an alphabet while run-length features (*f*3) also include information like the average width of letters, the density of writing, the structure of letters, the average size of letters, the position of characters, the regions enclosed inside the letters, inter and intra word spaces and the overall regularity of handwriting. These attributes are more linked to writing style of an individual (which stays the same across different scripts) rather than the script understudy. That is why these features outperform the state-of-the-art methods especially once the two writings to be compared are not in the same script.
- Finally, the writer identification and verification results obtained clearly demonstrate the potential of the run-lengths features (*f*3) for writer recognition from short handwriting images. These results also support the idea proposed in this paper i.e., writers share some characteristics across different scripts and one can identify the writer from samples written in a different script than those used for training.

After having discussed these performances, in the next section, we present the study on the stability of these features.

5.3. Stability of features

One of the most important parameters that influence the performance of writer identification and verification systems is the available amount of text in the writing samples for each writer. To study how the performance of the proposed run-length features varies with varying the amount of text, we evaluated the system by using one word, five words, one line, two lines and the complete paragraph (3 or more lines) for each of the writers. The results of these experiments are summarized in Fig. 3. Naturally, the performance is on the lower side for small amounts of text. In some cases, the performance curves begin to stabilize from two lines of text. These observations are consistent with (Siddiqi and Vincent, 2010) where the authors report 'acceptable' results on three lines of text on the IAM data set (Marti and Bunke, 2002).

Presence of noise in the documents under study is also an important parameter that can significantly affect the performance of run length features on writer identification and verification. To study the sensitivity of these features to noise in the image, we added (salt and pepper) noise of varying density to the documents in our data base. The noise density is varied from 1% to 5% of the total pixels in the image generating five sets of data for our experiments. The results of identification and verification on noisy images are summarized in Fig. 4. Naturally, there is a gradual degradation of performance as the noise density increases indicating the sensitivity of the run-length features to noise. The system fails to recognize a considerable number of writers in the presence of a reasonable noise. It should however be noted that these experiments were aimed at studying the effect of noise on these features. For practical applications, the noise can be removed from the documents as a preprocessing step prior to the computation of these features.

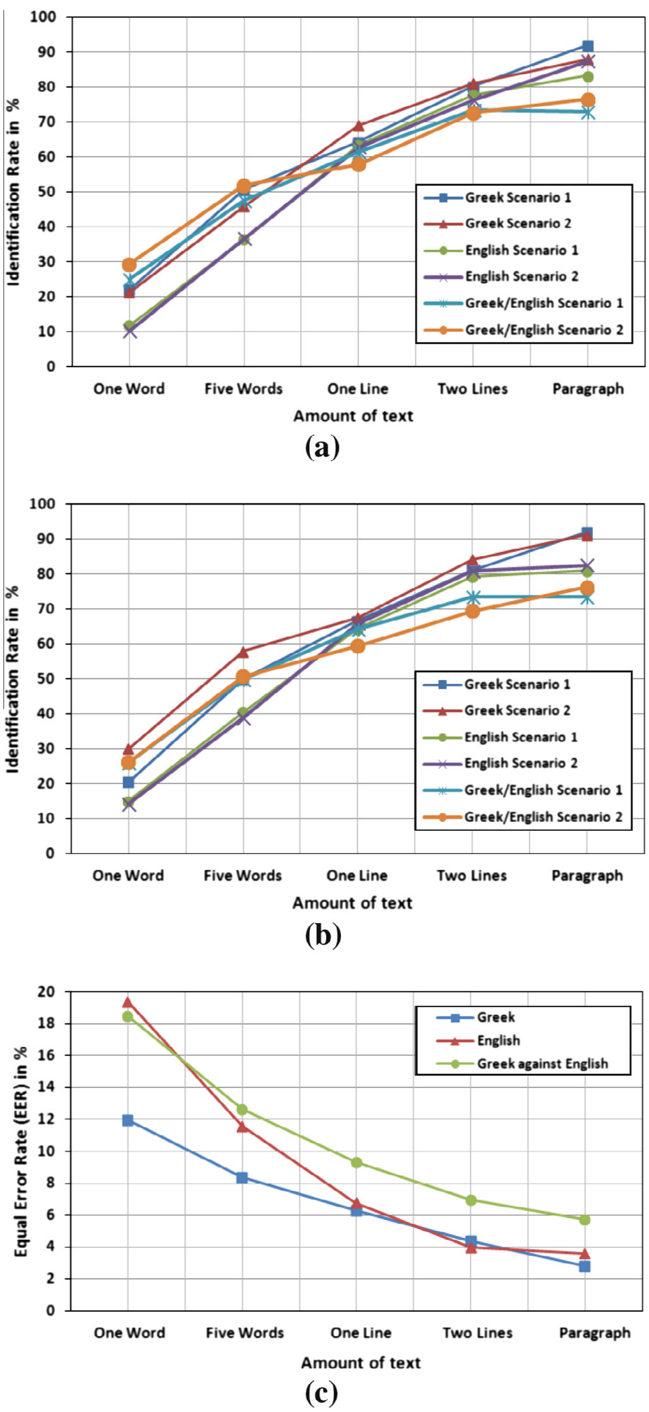

Fig. 3. Performance on different amounts of text: (a) SVM identification rates (b) KNN identification rates (c) equal error rates.

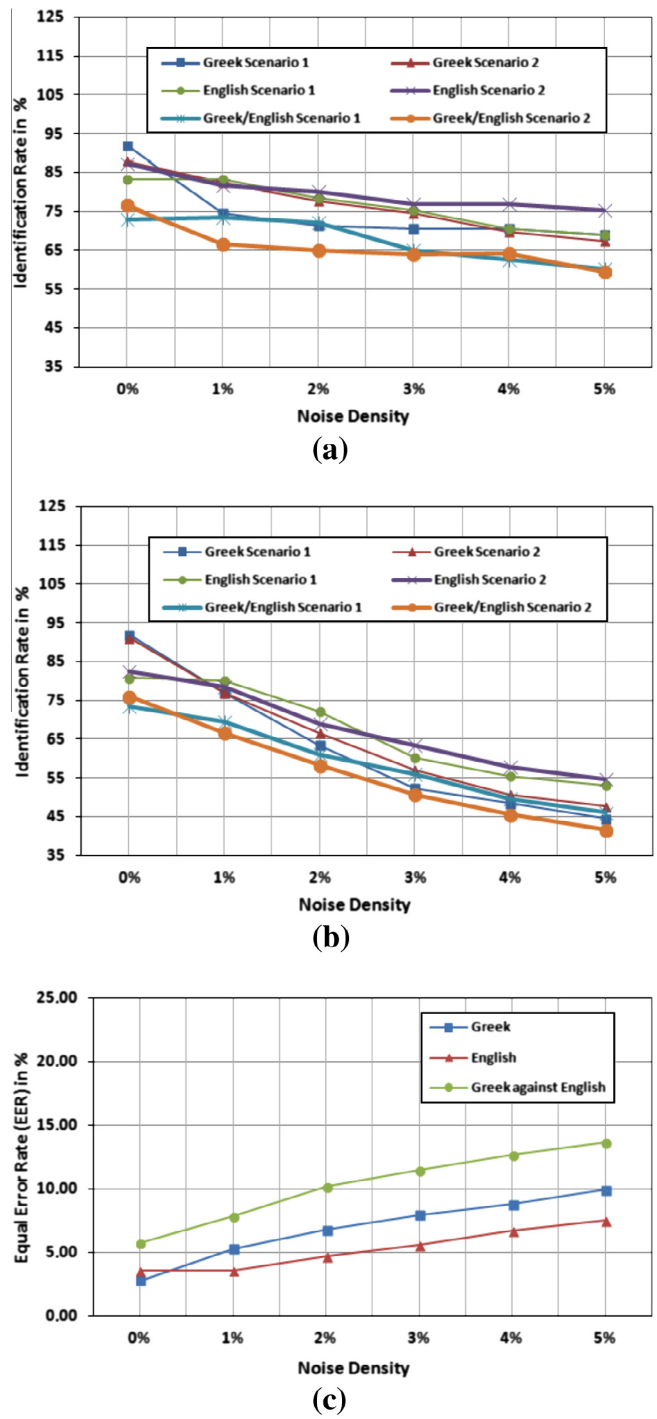

Fig. 4. System performance as a function of noise density: (a) SVM identification rates (b) KNN identification rates (c) equal error rates.

6. Conclusion and perspectives

This research was aimed at investigating multi-script text-independent writer identification and verification. We have employed a set of run-length features which have shown promising results on a database of handwritten documents in two different languages, Greek and English. To the best of our knowledge, this is the first study of its type that involves multi-script texts in the true sense. The evaluations were carried out on the only existing database of its type containing short writing samples from 126 different writers (Louloudis et al., 2012). The identification and verification results achieved are very encouraging. They reflect the effectiveness of the run-length features in a multi-script environment and validate the hypothesis put forward in this research, i.e., the writing style remains approximately the same across different scripts. It is also worth mentioning that, unlike most of the studies which use complete pages of text, our results are based on a limited amount of handwritten text, which, in fact, is closer to the real world scenarios.

Another interesting aspect of this study was the evaluation and comparison of a number of state-of-the-art methods on this data set. The features used in these methods naturally show a decrease in the performance when exposed to a multi-script scenario. In all cases, the run-length features outperform these features. It would be interesting to evaluate these features on relatively larger datasets with a large number of writers and many scripts per writer. This however is a challenging task to find individuals who are familiar with multiple scripts. To extend this study further, we intend to constitute a database including writing samples in Arabic and French provided by the same writer. In addition, classifiers other than those discussed in this paper can be evaluated to see how they perform in a multi-script environment. The proposed approach can also be extended to include a rejection threshold to reject writers that are not a part of the database. Finally, it would be interesting to apply some feature selection strategy to reduce the dimension of the proposed feature set and study which subset of features is the most discriminative in characterizing the writers. These orientations will make the subject of our future research on writer recognition.

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