ICDAR2013 Competition on Writer Identification

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***Abstract* - Writer identification is important for forensic analysis, helping experts to deliberate on the authenticity of documents. The ICDAR2013 Competition on Writer Identification is part of a competition series (see also ICDAR2011 and ICFHR2012 Writer Identification Contests) which is dedicated to record recent advances in the field of writer identification for Latin scripts using established evaluation performance measures. The benchmarking dataset was created with the help of 250 writers that were asked to copy four parts of text in two Latin based languages (English and Greek). This paper describes the contest details including the evaluation measures used as well as the performance of the 12 submitted methods by 6 different groups along with a short description of each method.**

Keywords - Writer Identification, handwritten document image processing, performance evaluation.

I. INTRODUCTION

Writer identification concerns the process of defining the writer of a document when a document database with known writer information is available. From the document image analysis scope, writer identification can be defined as the retrieval of handwritten samples of the same writer from a database, using a handwritten sample as a query. The growing number of recent publications ([1]-[7]), as well as the successful organization of several competitions ([8]-[10]) prove that writer identification is a very challenging and active area of research.

Following the successful organization of the "ICDAR2011 Writer Identification Contest" [8] and "ICFHR2012 Writer Identification Contest Challenge1: Latin Documents" [9], we organized the "ICDAR2013 Competition on Writer Identification" on the framework of the ICDAR2013 providing a new benchmarking dataset along with an objective and established evaluation methodology conference in order to record recent advances in the field of writer identification for Latin scripts. This benchmarking dataset was created with the help of 250 writers that were asked to copy four parts of text in two languages (two in English and two in Greek, see Figure 1) in order to test and compare recent algorithms for writer identification in realistic circumstances. The total number of document images of the benchmarking dataset was 1000.

These parts of text were the same for 200 writers. The remaining part of the benchmarking dataset (50 writers) was acquired using data created for the testing phase of the ICDAR2013 Handwriting Segmentation Contest [11]. In more detail, the Latin subset of the testing dataset of the ICDAR2013 Handwriting Segmentation Contest was created with the help of 50 writers which were asked to copy two parts of text (one for English and the other for Greek). From each part (English and Greek) we cropped two pieces of text each containing four text lines, thus resulting in four parts of text per writer.

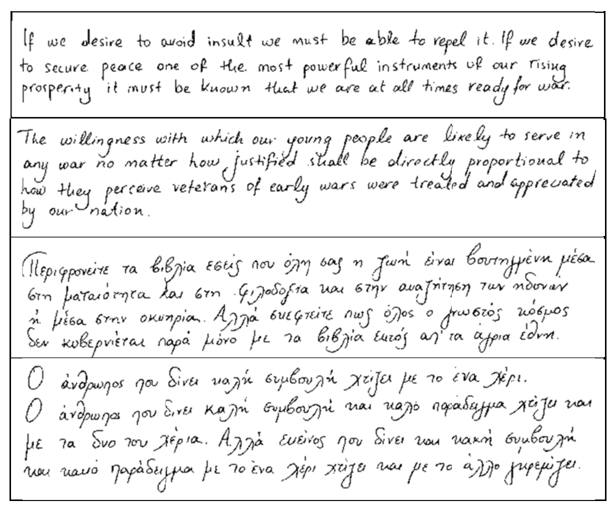

Figure 1. Image samples from the same writer included in the benchmarking dataset written in English and Greek language.

Among all documents, only the Greek documents were written in the native language of the writer. It should be noted that the number of text lines that were produced by the writers ranged between two and six.

The contest procedure was based on the following milestones. The authors of candidate methods registered their interest in the competition and downloaded the experimental dataset (the benchmarking dataset of the "ICFHR 2012 Writer Identification Contest, Challenge1: Latin Documents" containing 400 images written by 100 individual writers in English and Greek languages). At a next step, all registered participants were required to submit two executables in the

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form of a console application. The first executable was related to feature extraction whereas the second to the computation of the similarity between two feature vectors which correspond to two handwritten document images. After the evaluation of all candidate methods, the benchmarking dataset (1000 images along with the corresponding writer id information) became publicly available [12].

The remainder of the paper is organized as follows. In Section II, the participating groups together with a brief description of each method are summarized. Section III describes the performance evaluation protocol that was used while Section IV presents the experimental results of the competition. Finally, conclusions are drawn in Section V.

II. Methods And Participants

Six research groups submitted their methods to the contest. Several groups submitted multiple methods making the total number of participating methods equal to twelve. A brief description of these methods along with information of the participating groups is provided in this section.

CS-UMD-a method: Submitted by Rajiv Jain and David Doermann from the University of Maryland, College Park, USA and based on [15].

This approach splices words into "character-like" segments using seam cuts. These segments are described using gradients taken from their contour to form a feature vector. At a next step, features are clustered to find a representative character set. The feature vectors sets taken from the cluster centers from two images are compared to determine similarity.

CS-UMD-b method: Submitted by the same group as the previous method and also based on [15].

This approach is similar to the previous approach and the only difference is related to the way of splitting words. In this method, the splitting is accomplished using vertical cuts instead of making use of seam cuts.

CS-UMD-c method: Submitted by the same group as the previous method and based on [16].

In this method, K-adjacent segment (KAS) features are used in a bag-of-features (BOF) framework to model a user's handwriting. A BOF model is used to compare the writers from two documents by converting the KAS features extracted from a document into a histogram of code words.

Once a codebook is constructed, the source document is represented by a histogram of KAS "code words" present in the document. This histogram is normalized to sum up to one so that the histogram is invariant to the size of the input. The two histograms are compared using the Euclidean distance.

CVL-IPK method: Submitted by Stefan Fiel and Robert Sablatnig from the Computer Vision Lab, Vienna University of Technology, Austria and Fraunhofer IPK, Institute for Production Systems and Design Technology, Berlin, Germany and based on [17].

The method uses SIFT features and the Fisher Vector. The calculated features of a training set are clustered using a Gaussian Mixture Model to build a vocabulary which is the basis to calculate the Fisher Vector of each image. As a final step, the method uses the cosine distance to calculate the writer similarity between two document images.

HANNOVER-a method: Submitted by Karl-Heinz Steinke from the Hochschule Hannover, University of Applied Sciences and Arts, Germany and based on [20].

The submitted method is a statistical approach. The handwriting is seen as a texture with a steady structure of line elements all over the image. For the description of such a texture a suitable set of primitive elements has to be found whose frequency of occurrence is suited to distinguishing different writers to the greatest possible extent. The line segments of which the writing is composed can be considered as primitive elements of a handwriting specimen. Straight line segments may be obtained by the run lengths of pixel chains. The number and length of pixel chains is determined in eight different directions and for each direction a frequency distribution is calculated. The features obtained by this shift-invariant transformation are nearly text independent as long as there is enough text at hand. The feature vector furnishes information about the sloping position, size, regularity and roundness of the handwriting. Also, primitive elements from the background in the neighborhood of the handwriting are considered. The final feature vector contains 128 features. To compare two document images in terms of writer similarity, the cityblock distance is used.

HANNOVER-b method: Submitted by the same group as the previous method.

Since the feature vector obtained by the abovementioned method has a very high dimension (128 features), a dimensionality reduction of the feature vector is considered in this approach. As neighboring components of the feature vector are strongly correlated, they are added to a certain degree so that only 8 features in each direction remain. The final feature vector used has 64 components. The Mahalanobis distance between two feature vectors is used in order to compare two document images.

HIT-ICG method: Submitted by Xiangqian Wu and Youbao Tang from the Image Computing Group of School of Computer Science and Technology, Harbin Institute of Technology (HIT-ICG), Harbin, China.

This method adopts two feature sets based on scale-invariant feature transform (SIFT) for writer identification. The first feature set (SDS) is extracted by using the SIFT descriptors and a codebook constructed from training SIFT descriptors by SOM. The second feature set is a scale and orientation histogram (SOH) generated by using the scales and orientations of SIFT key points. The Chi-square distance is implemented for writer similarity measurement. A direct feature combination by simple distance weighted sum is calculated for the final decision.

QATAR-a method: Submitted by Abdelâali Hassaïne and Somaya Al-Maadeed from the Pattern Recognition and Image Processing Research Group of Qatar University and based on [13].

The method combines the geometrical features described in [13] through a logistic regression classifier. Those features are based on tortuosities, directions, curvatures, chain codes and edge based directional features.

QATAR-b method: It is the second method submitted by Abdelâali Hassaïne and Somaya Al-Maadeed and based on [14].

This method uses the most discriminant features among those described above after training them on both the provided experimental dataset of the competition as well as on the QUWI dataset [14].

TEBESSA-a method: Submitted by Chawki Djeddi from the Department of Mathematics and Computer Science, University of Tebessa, Algeria, Labiba Souici-Meslati from the Department of Computer Science, LRI Laboratory, Badji Mokhtar University, Annaba, Algeria, Abdellatif Ennaji from the LITIS Laboratory, Rouen University, France and Imran Siddiqi from Department of Computer Science, Bahria University, Islamabad, Pakistan and based on [18].

The method is based on multi-scale run length features [18] which are determined on the binary image taking into account both black and white pixels. The probability distribution of black and white run-lengths has been used. There are four scanning methods: horizontal, vertical, left-diagonal and right-diagonal. The run lengths features are calculated using the grey level run length matrices and the histogram of run lengths is normalized and interpreted as a probability distribution. The method considers the four direction white and black run-lenghts extracted from the original image. To compare two document images, the Manhattan distance metric is used.

TEBESSA-b method: Submitted by the same group as the previous method.

This method is based on the edge-hinge features which estimate the joint distribution of edge angles in a writer's handwriting. The edge-hinge features are constructed by performing edge detection, after applying a Sobel kernel on the input images, and subsequently, measuring the angles of both edge segments that emanate from each edge pixel. To compare two document images, the Manhattan distance metric is used.

TEBESSA-c method: Submitted by the same group as the previous method and based on [19].

This method is based on the combination of both types of features used by the previous two methods (multi-scale edge-hinge features and multi-scale run-length features [19]). Again for this method, the Manhattan distance metric is used to compare two document images.

III. PERFORMANCE EVALUATION

In order to measure the accuracy of the submitted methodologies we use the soft *TOP-N* and the hard *TOP-N* criterion. For every document image of the benchmarking dataset we calculate the distance to all other document images of the dataset using the participants' submitted executables. Then, we sort the results from the most similar to the less similar document image.

For the soft *TOP-N* criterion, we consider a correct hit when **at least one** document image of the same writer is included in the *N* most similar document images. Concerning the hard *TOP-N* criterion, we consider a correct hit when **all** *N* most similar document images are written by the same writer. For all 1000 document images of the benchmarking dataset we count the correct hits. The quotient of the total number of correct hits to the total number of the document images in the benchmarking dataset corresponds to the *TOP-N* accuracy. The values of *N* used for the soft criterion are 1, 2, 5 and 10 while for the hard criterion are 2 and 3. Since we have 4 document images per writer, 3 is the maximum value of *N* for the hard criterion.

For each criterion (soft or hard), we calculate the ranking of every submitted method. The final ranking is calculated after sorting the accumulated ranking value for all criteria (as in [8,9]). Specifically, let *R(j)* be the rank of the submitted method for the j^{th} criterion, where $j=1\ldots m$, m denotes the total number of criteria. As denoted in (1), for each writer identification method, the final ranking *S* is achieved by the *m* rankings summation. The smaller the value of *S* the better performance is achieved by the corresponding method.

$$S = \sum_{j=1}^{m} R(j) \tag{1}$$

IV. EVALUATION RESULTS

Three different experiments were conducted in order to measure the performance of the participating methods. For the first experiment, the participating methods were tested using the entire benchmarking dataset containing 1000 document images. The second experiment was conducted using only the Greek part of the benchmarking dataset (500 images). Finally, the last experiment considered only the English part of the benchmarking dataset (500 images). The evaluation results of all participating methods using the entire dataset and the soft *TOP-N* and the hard *TOP-N* criterion described in the previous section are presented in Tables I and II while the evaluation results for each language independently are presented in Tables III (Greek) and IV (English). In all tables, the results that correspond to the highest accuracy are marked in bold. Also, the ranking position of each method is presented in parentheses. Concerning language dependent experiments only the soft *TOP-N* criterion is feasible since only two documents are available per writer and the one is used as query.

TABLE I. SOFT EVALUATION ACCURACY USING ENTIRE DATASET (%)

Method	***TOP-1***	***TOP-2***	***TOP-5***	***TOP-10***
CS-UMD-a	**95,1 (1)**	**97,7 (1)**	**98,6 (1)**	99,1 (2)
CS-UMD-b	95 ,0 (2)	97,2 (2)	**98,6 (1)**	**99,2 (1)**
CS-UMD-c	85,5 (10)	90,9 (10)	95,0 (7)	96,8 (8)
CVL-IPK	90,9 (6)	93,6 (7)	97,0 (4)	98,0 (5)
HANNOVER-a	86,9 (9)	91,9 (9)	95,4 (6)	97,0 (7)
HANNOVER-b	91,5 (5)	94,2 (6)	97,0 (4)	98,0 (5)
HIT-ICG	94,8 (3)	96,7 (3)	98,0 (2)	98,3 (4)
QATAR-a	54,8 (12)	67,3 (12)	80,8 (9)	88,3 (10)
QATAR-b	78,4 (11)	85,8 (11)	91,5 (8)	95,1 (9)
TEBESSA-a	90,3 (7)	94,4 (5)	96,7 (5)	98,3 (4)
TEBESSA-b	90,1 (8)	93,4 (8)	97,0 (4)	97,9 (6)
TEBESSA-c	93,4 (4)	96,1 (4)	97,8 (3)	98,5 (3)

TABLE II. HARD EVALUATION ACCURACY USING ENTIRE DATASET (%)

Method	*TOP-2*	*TOP-3*
CS-UMD-a	19,6 (11)	7,1 (9)
CS-UMD-b	20,2 (10)	8,4 (8)
CS-UMD-c	21,2 (9)	5,7 (10)
CVL-IPK	44,8 (7)	24,5 (6)
HANNOVER-a	50,0 (6)	26,1 (5)
HANNOVER-b	54,3 (5)	27,3 (4)
HIT-ICG	**63,2 (1)**	**36,5 (1)**
QATAR-a	11,8 (12)	3,9 (11)
QATAR-b	34,6 (8)	16,5 (7)
TEBESSA-a	58,2 (3)	33,2 (2)
TEBESSA-b	55,5 (4)	29,5 (3)
TEBESSA-c	62,6 (2)	**36,5 (1)**

TABLE III. SOFT EVALUATION ACCURACY USING ONLY THE GREEK DOCUMENTS OF THE DATASET (%)

Method	*TOP-1*	*TOP-2*	*TOP-5*	*TOP-10*
CS-UMD-a	**95,6 (1)**	**98,2 (1)**	98,6 (2)	**99,2 (1)**
CS-UMD-b	95,2 (2)	97,6 (2)	**98,8 (1)**	99,0 (2)
CS-UMD-c	86,0 (10)	90,6 (9)	94,6 (9)	96,4 (6)
CVL-IPK	88,4 (7)	92,0 (7)	96,8 (5)	97,8 (4)
HANNOVER-a	86,4 (9)	91,2 (8)	95,2 (8)	97,4 (5)
HANNOVER-b	90,2 (6)	92,8 (6)	95,6 (7)	97,4 (5)
HIT-ICG	93,8 (3)	96,4 (3)	97,2 (4)	97,8 (4)
QATAR-a	58,8 (12)	66,6 (11)	79,6 (11)	85,8 (8)
QATAR-b	78,8 (11)	84,6 (10)	91,2 (10)	94,4 (7)
TEBESSA-a	91,0 (5)	94,0 (5)	96,8 (5)	97,8 (4)
TEBESSA-b	87,2 (8)	92,0 (7)	96,4 (6)	97,8 (4)
TEBESSA-c	92,6 (4)	96,0 (4)	98,0 (3)	98,4 (3)

TABLE IV. SOFT EVALUATION ACCURACY USING ONLY THE ENGLISH DOCUMENTS OF THE DATASET (%)

Method	*TOP-1*	*TOP-2*	*TOP-5*	*TOP-10*
CS-UMD-a	**94,6 (1)**	**97,0 (1)**	**98,4 (1)**	98,8 (2)
CS-UMD-b	94,4 (2)	96,6 (2)	**98,4 (1)**	**99,0 (1)**
CS-UMD-c	86,4 (7)	90,4 (9)	93,2 (8)	96,0 (7)
CVL-IPK	91,4 (4)	94,2 (4)	95,8 (4)	97,2 (3)
HANNOVER-a	84,6 (10)	88,6 (10)	92,0 (9)	94,0 (9)
HANNOVER-b	85,6 (9)	90,6 (8)	93,6 (7)	95,6 (8)
HIT-ICG	92,2 (3)	94,6 (3)	96,4 (2)	96,8 (4)
QATAR-a	50,0 (12)	64,2 (12)	78,0 (11)	85,4 (11)
QATAR-b	75,8 (11)	84,6 (11)	90,4 (10)	93,6 (10)
TEBESSA-a	86,0 (8)	91,6 (6)	94,4 (6)	96,0 (7)
TEBESSA-b	88,2 (6)	90,8 (7)	94,6 (5)	96,2 (6)
TEBESSA-c	91,2 (5)	93,4 (5)	96,2 (3)	96,6 (5)

Table V presents the ranking of all participating algorithms for each experiment independently as well as the final ranking. Note that columns *T1*, *T2*, *T3* and *T4* correspond to the ranking summation of Tables I, II, III and IV, respectively. The best overall performance is achieved by CS-UMD-a method which has been submitted by Rajiv Jain and David Doermann from the University of Maryland, College Park, USA.

TABLE V. OVERALL RANKING *S* FOR ALL EXPERIMENTS PRESENTED IN TABLES I TO IV RESPECTIVELY

Method	*T1*	*T2*	*T3*	*T4*	*S*	*OVERALL RANK*
CS-UMD-a	5	20	5	5	35	**1**
CS-UMD-b	6	18	7	6	37	**2**
CS-UMD-c	35	19	34	31	119	**10**
CVL-IPK	22	13	23	15	73	**6**
HANNOVER-a	31	11	30	38	110	**9**
HANNOVER-b	20	9	24	32	85	**8**
HIT-ICG	12	2	14	12	40	**3**
QATAR-a	43	23	42	46	154	**12**
QATAR-b	39	15	38	42	134	**11**
TEBESSA-a	21	5	19	27	72	**5**
TEBESSA-b	26	7	25	24	82	**7**
TEBESSA-c	14	3	14	18	49	**4**

The ranking list for the first three methodologies is:

1. CS-UMD-a (S = 35)
2. CS-UMD-b (S = 37)
3. HIT-ICG (S = 40)

Figure 2 presents the final ranking of all participating algorithms in terms of *S* with *m*=14 (experiments presented in Tables I-IV).

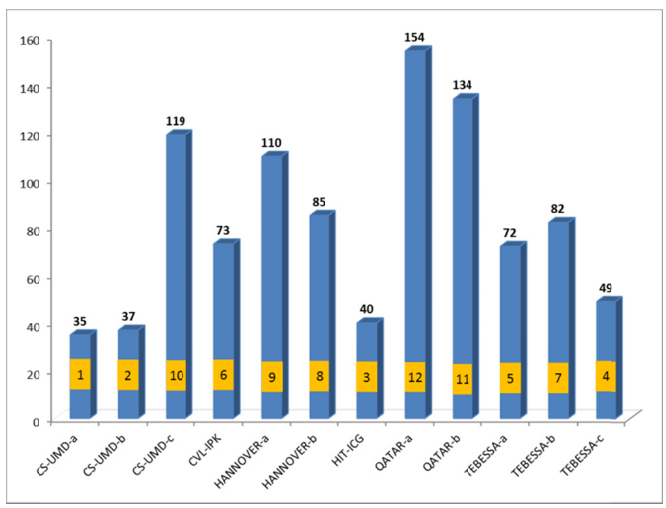

Figure 2. Final ranking in terms of *S*. The smaller the value of *S* the better performance is achieved by the corresponding method.

After a careful analysis of the data presented in Tables I to IV we can stress that:

a. The winning method (CS-UMD-a) outperforms all other methods on the *TOP-1*, *TOP-2* cases of the soft criterion and is ranked among the top two on the cases of *TOP-5*, *TOP-10* of the soft criterion. However, this method performs poorly on the two cases of the hard criterion (it is only ranked 11^{th} and 9^{th}, respectively).

b. None of the participating methods manages to achieve 100% accuracy on any criterion. In fact the highest accuracy achieved is 99,2% for the soft *TOP-10* criterion when using the entire dataset. This behaviour can be justified due to the large number of different writers included in the benchmarking dataset as well as to the similarity of the writing styles among different writers.

c. The third method (HIT-ICG) outpefroms all other methods on all cases of the hard criterion. Also, it is ranked among the top methods on all cases of the soft criterion.

d. The winning method's accuracies are very close to the winning method of the previous competition [9] (above 90% for the TOP-1 case) although the number of writers included in the benchmarking dataset have increased (from 100 writers in [9] to 250 writers in this competition).

e. It seems that the main drawback of all submitted methods is their difficulty to cluster all documents provided by the same writer at the top of the ranking list (see hard TOP-3 criterion). The highest accuracy performed for this criterion is 36,5% which implies that there exists a great potential for improvement.

f. If we compare the accuracies of the participating methods we observe that in almost all cases the participating methods perform better for the Greek documents (Table III) than English documents (Table IV). This is probably due to the fact that the writers' native language is Greek.

V. CONCLUSIONS

The ICDAR2013 Competition on Writer Identification is dedicated to record recent advances in the field of writer identification for Latin documents using established evaluation performance measures. The benchmarking dataset of the contest was created with the help of 250 writers that were asked to copy four parts of text in two languages (English and Greek). In order to measure the accuracy of the submitted methodologies we used the soft TOP-N and the hard TOP-N criterion. Six research groups with twelve submitted methodologies participated in the contest. The best overall performance is achieved by CS-UMD-a method which has been submitted by Rajiv Jain and David Doermann from the University of Maryland, College Park, USA. The winning method is based on contour gradient features calculated on "character-like" segments produced by words using seam cuts [15].

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