ICDAR 2011 Writer Identification Contest

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Abstract—**ICDAR 2011 Writer Identification Contest is the first contest which is dedicated to record recent advances in the field of writer identification using established evaluation performance measures. The benchmarking dataset of the contest was created with the help of 26 writers that were asked to copy eight pages that contain text in several languages (English, French, German and Greek). This paper describes the contest details including the evaluation measures used as well as the performance of the 8 submitted methods along with a short description of each method.**

Keywords - Writer Identification, handwritten document image, performance evaluation

I. INTRODUCTION

Writer identification is a behavioral handwriting-based recognition modality which proceeds by matching unknown handwritings against a database of samples with known authorship and it is considered today as a hot and promising topic of research. Therefore, writer identification recently has been studied and it has a wide variety of applications, such as security, financial activity, forensic and used as access control. Especially, analysis of handwritten documents has great bearing on the criminal justice systems.

In this first International Writer Identification contest, we provide a benchmarking dataset along with an objective and established evaluation methodology in order to capture the efficiency of recent practices in handwritten document writer identification. We created a document image benchmarking dataset with the help of 26 writers that were asked to copy eight pages that contain text in several languages (English, French, German and Greek). All images were binary and did not include any non-text elements (lines, drawings, etc.) (see Fig. 1). Part of the benchmarking dataset was also used in the ICDAR 2009 Handwriting Segmentation Contest [1]. The authors of candidate writer identification methods registered their interest in the contest and downloaded an experimental dataset (image samples together with the writer id). At a next step, all registered participants were required to submit one executable that calculates the distance between two input handwritten document images in terms of writer similarity. After the evaluation of all candidate methods, the benchmarking dataset became publicly available [2].

The remainder of the paper is structured as follows: In the next Section, the participating methods are presented. In Section III, the performance evaluation methodology is described while the results of the competition are presented in Section IV. Finally, conclusions are drawn in Section V.

(a)

(b)

Figure 1. Image samples from the bechmarking dataset written in (a) Greek and (b) English language

II. METHODS AND PARTICIPANTS

Seven research groups submitted their methodologies to the contest. One of these research groups submitted two different methodologies making the total number of participating methodologies equal to eight. A brief description of these methodologies is provided in this section.

ECNU method: Submitted by Hai Liu and Yue Lu of the Department of Computer Science and Technology, East China Normal University (ECNU), Shanghai, China.

The submitted methodology uses contour directional features for the issue of text-independent writer identification. The contour directional features encode orientation and curvature information in a local grid around every edge pixel to give an intrinsic characteristic of the individual handwriting style. The improved weighted Chi-square metric is applied to measure the similarity of two handwritings.

QUQA-a method: Submitted by Abdelâali Hassaïne and Somaya Al-Ma'adeed from the Pattern Recognition and Image Processing Research Group of Qatar University and Ahmed Bouridane from Northumbria University and based on [3] and [4].

The submitted method uses the edge-based directional probability distribution features [3] and the grapheme features [4]. These methods have previously been applied for Arabic writer identification and for signature verification and have shown interesting results. The classification step is performed using a logistic regression classifier applied on the whole document directly.

QUQA-b method: It is the second methodology submitted by Abdelâali Hassaïne, Somaya Al-Ma'adeed and Ahmed Bouridane. The difference with respect to QUQA-a method is that the classification step is performed using a logistic regression classifier applied to the document after decomposing it into four blocks.

TSINGHUA method: Submitted by Lu Xu, Xiaoqing Ding and Liangrui Peng from State Key Laboratory of Intelligent Technology and Systems, Department of Electronic Engineering, Tsinghua University, Beijing, P.R.China.

The methodology adopts a grid microstructure feature approach (GMSF) which processes handwritten texts in multi-line. A set of microstructures are calculated using a moving grid window. The probability distribution of the microstructures forms the GMSF which describes the writing style. A method using variance weighted Chi-square distance is implemented for writer similarity measurement.

GWU method: Submitted by Gregory J. Werner from George Washington University and Ali Hassaïne from Qatar University.

The submitted methodology combines nine image features which are part of the image features provided by the ICDAR 2011 – Arabic Writer Identification Contest [5] (ThicknessLengthsCircleHist30, chaincodeHist_4, chaincode Hist_8, chaincode4order3_64, directions_hist2_8, directions_hist3_12, directions_hist4_16, directions_hist1a2_12 and directions_hist1a2a3a4_40). In order to compare two feature vectors, a modification of the Mahalanobis metric was used in order to have a zero value for two unrelated documents and a value approximating infinity for a perfect match.

CS-UMD method: Submitted by Rajiv Jain from the University of Maryland, College Park, USA and based on [6].

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 their Euclidean distance.

TEBESSA method: Submitted by Chawki Djeddi from Department of Mathematics and Computer Science, Cheikh Larbi Tebessi University, Tebessa, Algeria and Labiba Souici-Meslati, from Department of Computer Science, LRI Laboratory, Badji Mokhtar University, Annaba, Algeria and based on [7].

The probability distribution of black and white run-lengths in four directions (horizontal, vertical, left-diagonal and right-diagonal) has been used. The histogram of run lengths is normalized and interpreted as a probability distribution. The methodology considers horizontal and right-diagonal white run-lengths extracted from the original image as well as horizontal, vertical, left-diagonal and right-diagonal black run-lengths extracted from the image after applying Sobel edge detection to generate a binary image in which only the edge pixels are "on". To compare two documents, the Manhattan Distance Metric is used.

MCS-NUST method: Submitted by Imran A. Siddiqi from National University of Sciences & Technology, MCS-NUST, Pakistan.

The methodology is based on a set of features that capture orientation and curvature information in writing at different levels of observation. These features are computed starting from image contours represented by chain codes as well as by a set of polygons. A total of 14 features are extracted including histogram of chain code and their first and second order differentials, histograms of chain code pairs and triplets, histogram of curvature index, weighted and non-weighted histograms of slope and curvature of line segments approximating the contours. The distance between two documents is defined as the average of distances between all corresponding features.

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 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, 5 and 7. Since we have 8 document images per writer, 7 is the maximum value of N for the hard criterion.

For each criterion (soft or hard), we calculate the ranking of every submitted methodology. The final ranking is calculated after sorting the accumulated ranking value for all criteria (as in [8]). Specifically, let $R(j)$ be the rank of the submitted method for the jth criterion, where $j=1…m$, 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.

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

IV. EVALUATION RESULTS

We evaluated the performance of all participating algorithms using the soft TOP-N and the hard TOP-N criterion presented in the previous section. We applied two different evaluation scenarios. In the first scenario, we used the whole images of the dataset. The evaluation results of all participating methods using the entire dataset are presented in Tables I and II while the evaluation results for each language independently are presented in Tables III–VI. In all tables, the results that correspond to the highest accuracy are marked in bold. Also, the ranking position of each is methodology is presented in parentheses. Concerning language dependent experiments only soft TOP-N criterion was feasible. As it was mentioned in Section I, the benchmarking set was created with the help of 26 writers that were asked to copy eight pages that contain text in four languages (English, French, German and Greek). Among all documents, only the Greek documents were written in the native language of the writer. As it is observed, the participating methods achieved the lowest rates when only the Greek documents of the dataset were used.

Concerning the first evaluation scenario the TSINGHUA method outperforms all the other methodologies since it has the smaller value of S with m=23 (see Eq. (1)). The ranking list (Table XIII) for the first three methodologies is:

1. TSINGHUA (S =36)
2. CS-UMD (S =40)
3. MCS-NUST (S =42)

TABLE I. SOFT EVALUATION USING ENTIRE DATASET (%)

Method	TOP-1	TOP-2	TOP-5	TOP-10
ECNU	84,6 (7)	86,5 (6)	88,0 (4)	88,9 (4)
QUQA-a	90,9 (6)	94,2 (5)	98,1 (3)	99,0 (3)
QUQA-b	98,1 (4)	98,6 (3)	99,5 (2)	**100,0 (1)**
TSINGHUA	**99,5 (1)**	99,5 (2)	**100,0 (1)**	**100,0 (1)**
GWU	93,8 (5)	96,2 (4)	98,1 (3)	99,0 (3)
CS-UMD	**99,5 (1)**	99,5 (2)	99,5 (2)	99,5 (2)
TEBESSA	98,6 (3)	**100,0 (1)**	**100,0 (1)**	**100,0 (1)**
MCS-NUST	99,0 (2)	99,5 (2)	99,5 (2)	99,5 (2)

TABLE II. HARD EVALUATION USING ENTIRE DATASET (%)

Method	TOP-2	TOP-5	TOP7
ECNU	51,0 (8)	2,9 (8)	0,0 (6)
QUQA-a	76,4 (7)	42,3 (7)	20,2 (5)
QUQA-b	92,3 (4)	77,4 (5)	41,4 (2)
TSINGHUA	95,2 (2)	**84,1 (1)**	41,4 (2)
GWU	80,3 (6)	44,2 (6)	20,2 (5)
CS-UMD	91,8 (5)	77,9 (4)	22,1 (4)
TEBESSA	**97,1 (1)**	81,3 (2)	**50,0 (1)**
MCS-NUST	93,3 (3)	78,9 (3)	38,9 (3)

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

Method	TOP-1	TOP-2	TOP-5	TOP-10
ECNU	19,2 (8)	19,2 (6)	19,2 (5)	21,2 (5)
QUQA-a	76,9 (7)	86,5 (5)	96,2 (2)	98,1 (2)
QUQA-b	90,4 (4)	90,4 (3)	92,3 (3)	94,2 (4)
TSINGHUA	92,3 (3)	94,2 (2)	**98,1 (1)**	**100,0 (1)**
GWU	80,8 (6)	86,5 (5)	90,4 (4)	94,2 (4)
CS-UMD	**96,2 (1)**	**96,2 (1)**	96,2 (2)	96,2 (3)
TEBESSA	84,6 (5)	88,5 (4)	90,4 (4)	94,2 (4)
MCS-NUST	94,2 (2)	94,2 (2)	96,2 (2)	96,2 (3)

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

Method	TOP-1	TOP-2	TOP-5	TOP-10
ECNU	15,4 (6)	15,4 (5)	15,4 (4)	17,3 (4)
QUQA-a	78,9 (5)	84,6 (4)	96,2 (3)	96,2 (3)
QUQA-b	**100,0 (1)**	**100,0 (1)**	**100,0 (1)**	**100,0 (1)**
TSINGHUA	96,2 (3)	96,2 (2)	98,1 (2)	**100,0 (1)**
GWU	84,6 (4)	88,5 (3)	96,2 (3)	98,1 (2)
CS-UMD	98,1 (2)	**100,0 (1)**	**100,0 (1)**	**100,0 (1)**
TEBESSA	96,2 (3)	96,2 (2)	98,1 (2)	**100,0 (1)**
MCS-NUST	96,2 (3)	96,2 (2)	98,1 (2)	**100,0 (1)**

TABLE V. SOFT EVALUATION USING ONLY THE FRENCH DOCUMENTS OF THE DATASET (%)

Method	TOP-1	TOP-2	TOP-5	TOP-10
ECNU	23,1 (6)	23,1 (5)	23,1 (3)	26,9 (2)
QUQA-a	94,2 (4)	96,2 (3)	96,2 (2)	**100,0 (1)**
QUQA-b	98,1 (2)	98,1 (2)	**100,0 (1)**	**100,0 (1)**
TSINGHUA	96,2 (3)	98,1 (2)	**100,0 (1)**	**100,0 (1)**
GWU	96,2 (3)	96,2 (3)	**100,0 (1)**	**100,0 (1)**
CS-UMD	**100,0 (1)**	**100,0 (1)**	**100,0 (1)**	**100,0 (1)**
TEBESSA	92,3 (5)	94,2 (4)	**100,0 (1)**	**100,0 (1)**
MCS-NUST	**100,0 (1)**	**100,0 (1)**	**100,0 (1)**	**100,0 (1)**

TABLE VI.   Soft Evaluation Using Only The German Documents Of The Dataset (%)

Method	TOP-1	TOP-2	TOP-5	TOP-10
ECNU	46,2 (5)	46,2 (5)	46,2 (3)	46,2 (2)
QUQA-a	86,5 (4)	90,4 (4)	98,1 (2)	**100,0 (1)**
QUQA-b	**100,0 (1)**	**100,0 (1)**	**100,0 (1)**	**100,0 (1)**
TSINGHUA	**100,0 (1)**	**100,0 (1)**	**100,0 (1)**	**100,0 (1)**
GWU	92,3 (3)	94,2 (3)	98,1 (2)	**100,0 (1)**
CS-UMD	**100,0 (1)**	**100,0 (1)**	**100,0 (1)**	**100,0 (1)**
TEBESSA	94,2 (2)	98,1 (2)	**100,0 (1)**	**100,0 (1)**
MCS-NUST	**100,0 (1)**	**100,0 (1)**	**100,0 (1)**	**100,0 (1)**

In the second scenario, we cropped the images of the benchmarking dataset, preserving only the first two text lines, in order to decrease the amount of available information. Then, we repeated the same experiments as in the first scenario using the entire dataset as well as the images of each language independently. Tables VII – XII present the evaluation results of all participating algorithms. The evaluation results indicate significant degradation of performance of all participating algorithms compared to the first scenario.

In the second evaluation scenario, the TSINGHUA method again outperforms all other methodologies. The ranking list for the first three methodologies is:

1. TSINGHUA (S=25)
2. MCS-NUST (S=53)
3. TEBESSA (S=61)

Table XIII presents the ranking of all participating algorithms for each experiment independently as well as the final ranking. The best overall performance taking into account both scenarios is achieved by TSINGHUA method which has been submitted by L. Xu, X. Ding and L. Peng from State Key Laboratory of Intelligent Technology and Systems, Department of Electronic Engineering, Tsinghua University, Beijing, P.R.China. The ranking list for the first three methodologies is:

1. TSINGHUA (S=61)
2. MCS-NUST (S=95)
3. TEBESSA (S=113)

Figure 2 depicts the final ranking of all participating algorithms in term of S with m=46.

TABLE VII.   Soft Evaluation Using Entire Dataset Of Cropped Images (%)

Method	TOP-1	TOP-2	TOP-5	TOP-10
ECNU	65,9 (7)	71,6 (7)	81,7 (7)	86,5 (7)
QUQA-a	74,0 (4)	81,7 (4)	91,8 (4)	96,2 (3)
QUQA-b	67,3 (5)	79,8 (5)	91,8 (4)	94,7 (5)
TSINGHUA	**90,9 (1)**	**93,8 (1)**	**98,6 (1)**	**99,5 (1)**
GWU	74,0 (4)	81,7 (4)	91,4 (5)	95,2 (4)
CS-UMD	66,8 (6)	75,5 (6)	83,7 (6)	89,9 (6)
TEBESSA	87,5 (2)	92,8 (2)	97,6 (2)	**99,5 (1)**
MCS-NUST	82,2 (3)	91,8 (3)	96,6 (3)	97,6 (2)

TABLE VIII.   Hard Evaluation Using Entire Dataset Of Cropped Images (%)

Method	TOP-2	TOP-5	TOP-7
ECNU	39,4 (8)	2,9 (8)	0,0 (6)
QUQA-a	52,4 (4)	15,9 (7)	3,4 (5)
QUQA-b	47,6 (7)	22,6 (4)	6,3 (4)
TSINGHUA	**79,8 (1)**	**48,6 (1)**	12,5 (2)
GWU	51,4 (6)	20,2 (6)	6,3 (4)
CS-UMD	51,9 (5)	22,1 (5)	3,4 (5)
TEBESSA	76,0 (2)	34,1 (3)	**14,4 (1)**
MCS-NUST	71,6 (3)	35,6 (2)	11,1 (3)

TABLE IX.   Soft Evaluation Using Only The Greek Documents Of Cropped Images (%)

Method	TOP-1	TOP-2	TOP-5	TOP-10
ECNU	11,5 (7)	15,4 (8)	19,2 (8)	23,1 (7)
QUQA-a	44,2 (3)	51,9 (5)	73,1 (5)	90,4 (4)
QUQA-b	34,6 (6)	55,8 (4)	76,9 (4)	80,8 (5)
TSINGHUA	51,9 (2)	**71,2 (1)**	**98,1 (1)**	**98,1 (1)**
GWU	42,3 (4)	46,2 (6)	65,4 (7)	76,9 (6)
CS-UMD	40,4 (5)	44,2 (7)	67,3 (6)	76,9 (6)
TEBESSA	42,3 (4)	63,5 (3)	80,8 (3)	92,3 (3)
MCS-NUST	**55,8 (1)**	69,2 (2)	84,6 (2)	94,2 (2)

TABLE X.   Soft Evaluation Using Only The English Documents Of Cropped Images (%)

Method	TOP-1	TOP-2	TOP-5	TOP-10
ECNU	13,5 (8)	15,4 (8)	15,4 (6)	19,2 (5)
QUQA-a	55,8 (5)	67,3 (5)	75,0 (4)	82,7 (4)
QUQA-b	63,5 (4)	69,2 (4)	90,4 (2)	96,2 (2)
TSINGHUA	**76,9 (1)**	**90,4 (1)**	**96,2 (1)**	**100,0 (1)**
GWU	50,0 (6)	57,7 (6)	69,2 (5)	82,7 (4)
CS-UMD	44,2 (7)	50,0 (7)	69,2 (5)	82,7 (4)
TEBESSA	69,2 (2)	84,6 (2)	88,5 (3)	**100,0 (1)**
MCS-NUST	67,3 (3)	80,8 (3)	88,5 (3)	92,3 (3)

TABLE XI.   Soft Evaluation Using Only The French Documents Of Cropped Images (%)

Method	TOP-1	TOP-2	TOP-5	TOP-10
ECNU	46,2 (8)	46,2 (6)	46,2 (7)	46,2 (6)
QUQA-a	51,9 (6)	67,3 (5)	88,5 (4)	92,3 (3)
QUQA-b	48,1 (7)	67,3 (5)	84,6 (6)	88,5 (5)
TSINGHUA	**80,8 (1)**	**90,4 (1)**	**96,2 (1)**	**96,2 (1)**
GWU	57,7 (5)	69,2 (4)	86,5 (5)	92,3 (3)
CS-UMD	59,6 (4)	67,3 (5)	84,6 (6)	90,4 (4)
TEBESSA	63,5 (3)	78,9 (3)	90,4 (3)	94,2 (2)
MCS-NUST	65,4 (2)	82,7 (2)	92,3 (2)	**96,2 (1)**

TABLE XII. SOFT EVALUATION USING ONLY THE GERMAN DOCUMENTS OF CROPPED IMAGES (%)

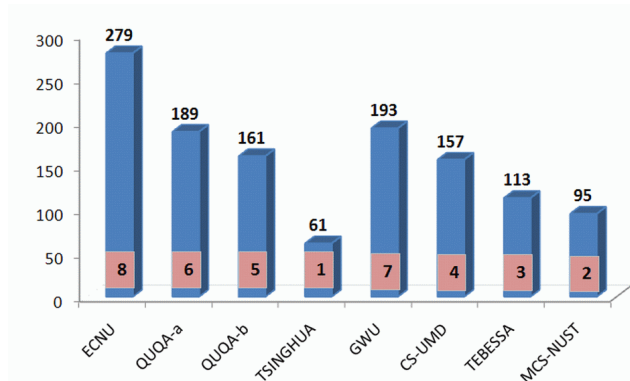| Method	TOP-1	TOP-2	TOP-5	TOP-10
ECNU	21,2 (7)	21,2 (8)	23,1 (7)	26,9 (6)
QUQA-a	71,2 (4)	78,9 (4)	86,5 (5)	94,2 (4)
QUQA-b	44,2 (6)	63,5 (7)	84,6 (6)	92,3 (5)
TSINGHUA	**84,6 (1)**	**90,4 (1)**	**96,2 (1)**	**100,0 (1)**
GWU	69,2 (5)	76,9 (5)	88,5 (4)	92,3 (5)
CS-UMD	73,1 (3)	80,8 (3)	90,4 (3)	96,2 (3)
TEBESSA	71,2 (4)	75,0 (6)	88,5 (4)	98,1 (2)
MCS-NUST	78,9 (2)	88,5 (2)	94,2 (2)	98,1 (2)

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

V. CONCLUSIONS

This first Writer Identification Contest is dedicated to record recent advances in the field of writer identification using established evaluation performance measures. The benchmarking dataset of the contest was created with the help of 26 writers that were asked to copy eight pages that contain text in several languages (English, French, German and Greek). In order to measure the accuracy of the submitted methodologies we used the soft TOP-N and the hard TOP-N criterion. Seven research groups with eight submitted methodologies participated in the contest and were evaluated based on two scenarios using the whole and part of the images in the benchmarking dataset. The best performance in both scenarios was achieved by the

TSINGHUA method submitted by L. Xu, X. Ding and L. Peng from State Key Laboratory of Intelligent Technology and Systems, Department of Electronic Engineering, Tsinghua University, Beijing, P.R.China. The winning method is based on a set of microstructure features which are calculated using a moving grid window.

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TABLE XIII. OVERALL RANKING IN TERMS OF S FOR ALL EXPERIMENTS. COLUMNS I TO XII CORRESPOND TO THE EXPERIMENTS PRESENTED IN TABLES I TO XII RESPECTIVELY.

Method	I	II	III	IV	V	VI	S [scenario 1]	VII	VII	IX	X	XI	XII	S [scenario 2]	S [scenario 1&2]	OVERALL RANK
ECNU	21	22	24	19	16	15	**117**	28	22	30	27	28	27	**162**	**279**	**8**
QUQA-a	17	19	16	15	10	11	**88**	15	16	17	18	17	18	**101**	**189**	**6**
QUQA-b	10	11	14	4	6	4	**49**	19	15	19	12	24	23	**112**	**161**	**5**
TSINGHUA	5	5	7	8	7	4	**36**	4	4	5	4	4	4	**25**	**61**	**1**
GWU	15	17	19	12	8	9	**80**	17	16	23	21	19	17	**113**	**193**	**7**
CS-UMD	7	13	7	5	4	4	**40**	24	15	24	23	12	19	**117**	**157**	**4**
TEBESSA	6	4	17	8	11	6	**52**	7	6	13	8	16	11	**61**	**113**	**3**
MCS-NUST	8	9	9	8	4	4	**42**	11	8	7	12	8	7	**53**	**95**	**2**