ICDAR 2011 Chinese Handwriting Recognition Competition

Cheng-Lin Liu, Fei Yin, Qiu-Feng Wang, Da-Han Wang
National Laboratory of Pattern Recognition (NLPR)
Institute of Automation of Chinese academy of Sciences, Beijing 100190, China
E-mail: {liucl, fyin, wangqf, dhwang}@nlpr.ia.ac.cn

Abstract **In the Chinese handwriting recognition competition organized with the ICDAR 2011, four tasks were evaluated: offline and online isolated character recognition, offline and online handwritten text recognition. To enable the training of recognition systems, we announced the large databases CASIA-HWDB/OLHWDB. The submitted systems were evaluated on un-open datasets to report character-level correct rates. In total, we received 25 systems submitted by eight groups. On the test datasets, the best results (correct rates) are 92.18% for offline character recognition, 95.77% for online character recognition, 77.26% for offline text recognition, and 94.33% for online text recognition, respectively. In addition to the evaluation results, we provide short descriptions of the recognition methods and have brief discussions.**

Keywords-Chinese handwriting recognition competition; isolated character recognition; handwritten text recognition; offline; online

I. Introduction

Chinese handwriting recognition, including online (stroke trajectory-based) and offline (image-based) recognition of both isolated characters and continuous texts, have received intensive attention. Despite the efforts in the past 40 years, the problem still remains un-solved, as evidenced by the low accuracies on freely written samples [1][2]. To stimulate the research in this field, the National Laboratory of Pattern Recognition (NLPR), Institute of Automation of Chinese Academy of Sciences (CASIA), released large databases of free handwriting CASIA-HWDB/OLHWDB [3], and organized a contest of handwritten Chinese character recognition in 2010 [2].

In this competition organized with the ICDAR 2011, we extend the evaluation tasks from offline/online isolated handwritten Chinese character recognition to handwritten text recognition as well. Specifically, there are four tasks: offline and online isolated character recognition, offline and online handwritten text recognition. By the deadline of final systems submission on May 31, we received 25 systems submitted by eight groups, including nine for offline isolated character recognition, nine for online isolated character recognition, three for offline text recognition and four for online text recognition.

All the submitted systems used the sample of our released databases CAISA-HWDB/OLHEDB for training, and some used additional private data or distorted data. On evaluation on un-open test datasets written by 60 persons, we rank the systems according to the character-level correct rate for both isolated character recognition and text recognition tasks. The best results (correct rates) are 92.18% for offline character recognition, 95.77% for online character recognition, 77.26% for offline text recognition, and 94.33% for online text recognition, respectively.

In the following, we first describe the databases and evaluation protocol in Section 2; Section 3 describes the recognition methods of the submitted systems; Section 4 presents the evaluation results and Section 5 provides concluding remarks.

II. Databases and Evaluation Protocal

For promoting the research of Chinese handwriting recognition, we recently releases the large databases CASIA-HWDB/OLHWDB [3], which are free for academic research. The competition participants were encouraged to use the released databases for training their recognition systems, and can use any additional private or open datasets and distorted samples for enhancement. We reserve the un-open test datasets for evaluating the submitted systems in competition, and rank the systems according to the character-level correct rate.

A. *CASIA Databases*

The databases CASIA-HWDB and CASIA-OLHWDB contain offline/online handwritten characters and continuous texts written by 1,020 persons using Anoto pen on papers, such that the online and offline data were produced concurrently. The samples include both isolated characters and handwritten texts (continuous scripts). Either the (offline) HWDB or the (online) OLHWDB contain six datasets: three for isolated characters (DB1.0–1.2) and three for handwritten texts (DB2.0–2.2). The datasets of isolated characters contain about 3.9 million samples of 7,356 classes (7,185 Chinese characters and 171 symbols), and the datasets of handwritten texts contain about 5,090 pages and 1.35 million character samples. All the data has been segmented and annotated at character level, and each dataset is partitioned into standard training and test subsets. More details of the databases can be found in [3].

B. *Test Datasets*

The test datasets which are unknown to all participants were collected for the Competition 2010 [2]. They were written by 60 writers who did not contribute to the released

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CASIA-HWDB/OLHWDB. The Competition 2010 only tested the isolated characters, however.

For evaluating isolated character recognition, we confine the character set to the 3,755 Chinese characters in the level-1 set of GB2312-80, which has been popularly tested in Chinese character recognition research. The handwritten text data was produced by hand-copying natural language texts on un-formatted pages. The texts in the test dataset are different from those in the databases CASIA-HWDB/OLHWDB. The characters in the texts are mostly within the set of 7,356 classes of the isolated character datasets (DB1.0-DB1.2) in CASIA-HWDB/OLHWDB. Table 1 shows the statistics of the test datasets, where #abnormal denotes the number of outlier characters. We can see that the online and offline data of concurrently written texts have slightly different numbers of character samples. This is because of some data loss in the digital ink or scanned images.

Fig. 1 shows a page of handwritten text in the test dataset.

Table 1. Statistics of the test datasets.

	Isolate characters		Continuous texts	
	online	offline	online	offline
#writer	60	60	60	60
#class	3,755	3,755	1,375	1,385
#text line			3,432	3,432
#sample	224,590	224,419	91,576	91,563
#Chinese	224,590	224,419	81,049	81,025
#symbol	0	0	10,487	10,502
#abnormal	0	0	40	36

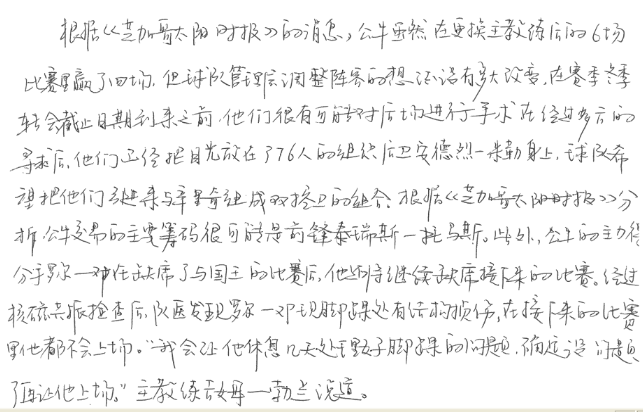
根据《芝加哥太阳时报》的消息，公牛虽然在更换主教练后的6场比赛里赢了四场，但球队管理层调整阵容的想法还没有多大改变，在赛季交易截止日期到来之前，他们很有可能对后场进行手术。在经过多方的寻求后，他们已经把目光放在了76人的组织后卫安德烈-米勒身上，球队希望把他迎来与辛里奇组成双控卫的组合。根据《芝加哥太阳时报》分析，公牛送出的主要筹码很可能是前锋泰瑞斯-托马斯。此外，公牛的主力得分手罗尔-邓在缺席了与国王的比赛后，他还将继续缺席接下来的比赛。经过核磁共振检查后，队医发现罗尔-邓脚踝处有结构损伤，在接下来的比赛里他都不会上场。"我会让他休息几天处理好脚踝的问题，确定没问题了再让他上场，"主教练吉姆-勃兰说道。

Fig. 1. A page of handwritten text.

C. *Performance Evaluation*

In isolated character recognition, the recognition systems read isolated character samples and output the classification results (top-rank class and top 10 classes) for each sample. The results are compared with the ground-truth to judge whether they are correct or not. The systems are ranked according to the correct rate, i.e., the percentage of correctly classified samples over all the test samples:

$$CR = N_C / N_I, \tag{1}$$

Where N_C is the number of correctly recognized samples, and N_I is the total number of test samples. We report the top-rank correct rate as well as the cumulated correct rate of top 10 classes.

For continuous text recognition, we provide handwritten pages with text lines segmented. The recognition systems output the result (text transcription, a character string) for each text line. We compare the output character string of each text line with its ground-truth by error-correcting string matching to count how many characters are correctly recognized. A correct rate (CR) and an accurate rate (AR) [1][4] are calculated over all the text lines in the test dataset:

$$\begin{aligned} CR &= (N_t - D_e - S_e) / N_t, \\ AR &= (N_t - D_e - S_e - I_e) / N_t, \end{aligned} \tag{2}$$

where N_t is the total number of characters in the ground-truth texts, the numbers of substitution errors (S_e), deletion errors (D_e) and insertion errors (I_e) are obtained by error-correcting string matching by dynamic programming (DP). The accurate rate AR takes into account the inserted characters, and can be negative if the text lines are seriously over-segmented.

III. Participating Systems

In the following, we give the brief descriptions of the submitted recognition systems provided by the developers.

A. *Offline Isolate Character Recognition (Task 1)*

This task received registrations from six groups, and finally, all the six groups completed their systems, submitted nine systems in total.

CASIA-CREC: The Character Recognition Engineering Center of CASIA (CASIA-CREC, jointly owned by CASIA and Hanvon Technology Ltd.) submitted three systems, using the same method but training with different datasets. After normalizing the character image using the modified centroid-boundary alignment (MCBA) method [5], 896D peripheral direction contributivity (PDC) feature is extracted [6] and is reduced to 128D by Fisher linear discriminant analysis (FLDA). For classification, nearest prototype classifiers were trained using the learning vector quantization (LVQ3) algorithm of Kohonen. The training datasets of three systems are: (1) GB1 (level-1 set of GB2312-80) samples of CASIA-HWDB1.0 and CASIA-HWDB1.1; (2) Samples of (1) plus Hanvon dataset 1 (about 10M samples); (3) Samples of (1) plus Hanvon dataset 2 (about 10M samples).

CASIA-CSIS: The Key Laboratory of Complex Systems and Intelligence Science of CASIA submitted a system, contributed by Yunxue Shao and Chunheng Wang. From a character image, it extracts 8-direction gradient direction features [7] after normalization using three methods: the line density normalization method [8], the dot density normalization method [9] and the bi-moment normalization method [10]. The obtained 1536D feature vector is reduced to 512D by FLDA, which is then classified by the MQDF2 [11] (number of principal eigenvectors k=60) and the CMF [12] for discriminating similar character pairs. The training set contains the GB1 samples in the CASIA-HWDB1.1.

HKU: The Department of Electrical and Electronic Engineering of University of Hong Kong (HKU) submitted a system, contributed by K.C. Leung and C.H. Leung based on the method [13]. The input grey level character image is first binarized and normalized by 2D nonlinear normalization method [8]. Then, 4-direction chaincodes are assigned to each boundary pixel. The four chaincode maps are filtered using a Gaussian mask to produce a vector of 484D features, which are then variable-transformed and reduced to a 256D vector by FLDA. The classifier is a regularized version of QDF (MQDF1 [11]) trained with both raw samples and distorted samples. The raw samples are the ones of GB1 in CASIA-HWDB1.0 and CASIA-HWDB1.1.

IDSIAnn: The Dalle Molle Institute for Artificial Intelligence (IDSIA), Switzerland, submitted two systems based on a flexible, high-performance GPU implementation of convolutional neural network (CNN) with nine hidden layers [14,15], implemented by Ueli Meier and Dan Ciresan. First, the character image is resized to 40x40 pixels and placed in the centre of a 48x48 image. Then each image is normalized independently and fed into the CNN. The training set of CASIA-HWDB1.1 was used for training and the test set of CASIA-HWDB1.1 was used for validation. The first system is the network that obtained the lowest error rate on the validation set, while the second one was obtained by retraining the first network for ten more epochs using all the data from CASIA-HWDB1.1. During training for both two networks, the training images were deformed with affine transformations: scaling ±10% of image size, translation ±10% of image size, and rotation ±10°, as well as elastic deformations.

SCUT-HCII: The Human-Computer Communication and Intelligent Interface Laboratory of SCUT (SCUT-HCII) submitted a system, contributed by Yan Gao, Lingyu Liang, Kai Ding and Lianwen Jin. The underlying method uses linear normalization and elastic meshing [16] to normalize the character image, then gradient features of 512D and Gabor features of 256D [17] are extracted and reduced to 160D by FLDA. Finally, the reduced vector is classified using the MQDF classifier (12 principal eigenvectors per class), with parameters compressed by subspace distribution sharing VQ (splitVQ) technique [18]. The training dataset contains the GB1 samples in CASIA-HWDB1.0 and CASIA-HWDB1.1.

THU: The Department of Electronic Engineering of Tsinghua University (THU) submitted a system, contributed by Yanwei Wang, Xiaoqing Ding, Changsong Liu, based on cascade classifiers. The gradient feature (588D) is extracted on gray image and reduced to 160D subspace by heteroscedastic linear discriminant analysis (HLDA) [19]. The main classifier is the basic modified quadratic discriminant function (MQDF) trained by a discriminative algorithm. The second MQDF classifier is used to correct the classification errors of the first one. The classifiers were trained on the GB1 samples in CASIA-HWDB1.0 and CASIA-HWDB1.1, and character samples extracted from the text data of CASIA-HWDB2.0-2.2.

B. *Online Isolate Character Recognition (Task 2)*

This task received registrations from seven groups, and finally, five groups submitted nine systems.

IDSIAnn: The two systems submitted by the IDSIA use the same CNN as in Task 1 by mapping the online character into an image from its coordinates of stroke trajectory. Then the image is resized to 40x40 pixels and placed in the center of a 48x48 image. Finally, the resulting image is fed into the CNN after smoothing with a Gaussian filter of 3x3 neighborhood and standard deviation of 0.75. The training set of CASIA-OLHWDB1.1 was used for training and the test set was used for validation. The first network is the one with the lowest error rate on the validation set, and the second one was obtained by retraining the first one for ten more epochs using all the data from CASIA-OLHWDB1.1.

SCUT-IntSig: The Human Computer Intelligent Interaction Joint Lab of SCUT and IntSig Information Ltd submitted two systems. SCUT-IntSig-onHCR-1 extracts 8-direction feature based on the method [20], and reduces the original 1024D feature to 160D by FLDA, and the reduced vector is classified by integrating a minimum distance classifier and a Time Delay Neural Network (TDNN) like classifier. SCUT-IntSig-onHCR-2 extracts modified 8-direction feature [21] of 1024D and gradient feature of 512D, the obtained 1536D feature vector is reduced to 160D by FLDA. On the reduced vector, 20 candidate classes selected by a minimum distance classifier are fed into an ensemble of two compact MQDF classifiers and a TDNN like classifier for discrimination. Both systems use the splitVQ technique to compress the parameters of classifiers, and used all the GB1 samples of SCUT-COUCH2009 [22] and CASIA-OLHWDB1.0-1.1 for training.

THU: The Department of Electronic Engineering of Tsinghua University (THU) submitted a system contributed by Yan Chen, Xiaoqing Ding and Changsong Liu. The system extracts 1928D 8-directional element features and some other kinds of features after nonlinear normalization. Then the extracted features are reduced to 200D by FLDA, and classified using an MQDF classifier trained with the GB1 samples in CACIA-OLHWDB1.0-1.1.

VO: The Vision Objects Ltd., France, submitted three systems, contributed by Zsolt Wimmer based on their MyScript technology. The system normalizes the digital ink of character by applying a B-spline approximation on the input stroke, then extracts the features integrating dynamic and static information. Dynamic features include such as the position, direction and curvature of the ink signal trajectory. Static features are computed from a bitmap representation of the ink and are typically based on projections and histograms. Finally the feature vector is fed into a simple Multilayer Perceptron (MLP) classifier. The training data includes the samples in CASIA-OLHWDB1.0-1.1, the GB1 samples in SCUT-COUCH2009 [22], some private data, as well as distorted samples. The three systems differ in the trade-offs between speed and recognition: the VO-1 is the fastest but slightly less accurate than the VO-3 which provides the highest accuracy. The VO-2 is a compromise between them.

XD_IIPR: The Intelligent Information Processing and Pattern Recognition Lab of Xidian University (XD-IIPR) submitted a system contributed by Chao Yao, Wei Hou, Shiyong Ma and Zhaoyang Lu. In its method, a character is mapped into an image and normalized into a 64x64 image by dot density equalization. After smoothing using a mean filter and adding imaginary strokes, 8-direction features (512D) are extracted and reduced to 180D by FLDA [20]. A minimum distance classifier is used to select 20 candidates, which are further classified by an MQDF classifier (10 principal components). The training dataset contains the GB1 samples from CASIA-OLHWDB1.0 and CASIA-OLHWDB1.1.

C. *Offline Handwritten Text Recognition (Task 3)*

For this task, three registered groups submitted three systems.

CASIA-CREC: The CASIA-CREC submitted a system. In this system, the text line is first split into components, and consecutive components are merged into candidate character blocks. N-best segmentation paths are selected from these candidate blocks based on the geometric information measured with an Adaboost classifier. Then, each selected segmentation path is scored by integrating recognition scores, linguistic context and geometric information, and the optimal segmentation path (recognition result) is searched by the Viterbi algorithm. The LVQ character classifier was trained on CASIA-HWDB2.0 plus Hanvon dataset (about 12M samples), the geometric model was trained on CASIA-HWDB2.1 and the language model was trained on the corpus (about 0.5G samples) collected by Hanvon.

SCUT-HCII: The SCUT-HCII submitted a system contributed by Yan Gao, Nanxi Li and Linawen Jin. In this system, curved segmentation paths are generated by the method of [23], then under a Bayesian-based probabilistic framework [24], multiple probabilistic scores (character model, language model and geometric context) are fused for text line recognition. They extracted the samples of 3,843 frequent Chinese characters and 171 symbols of CASIA-HWDB1.0-1.2 for training the character model. The language model was trained on a Chinese text corpus from the CLDC (Chinese Linguistic Data Consortium).

THU: The Department of Electronic Engineering of THU submitted a system contributed by Yanwei Wang, Xiaoqing Ding, and Changsong Liu. The system is based on an over-segmentation-and-merging method [25]. Each segmentation path is scored by integrating the character recognition model, linguistic context and geometric information. The optimal segmentation path is founded by dynamic programming search. The character recognition model is an MQDF classifier (3,957 classes, including 3,879 Chinese characters and 78 characters) trained on samples extracted from CASIA-HWDB1.0-1.1 and CASIA-HWDB2.0-2.2. The language model is a character bi-gram trained on a corpus of People's Daily.

D. *Online Handwritten Text Recognition (Task 4)*

This task received registrations from four groups, and finally, two groups submitted four systems.

SCUT-HCII: SCUT-HCII submitted a system contributed by Yan Gao, Kai Ding and Lianwen Jin. It is based on stroke segmentation and character over-segmentation. By integrating the character bi-gram language model and character model in the score of path segmentation, the recognition result is searched by partial dynamic programming. For training the character recognition model, they extracted the samples of 3,755 frequent Chinese characters and 171 symbols from CASIA-OLHWDB1.0 and CASIA-OLHWDB1.1. The language model was trained on a Chinese corpus from the CLDC (Chinese Linguistic Data Consortium).

VO: The three systems submitted by Vision Objects use three "experts" (segmentation, recognition, interpretation) collaborating through dynamic programming to process the digital ink and generate candidates at the character, word, and sentence level. The segmentation expert constructs a segmentation graph where each node corresponds to a character hypothesis and adjacency constraints between characters are handled by the node connections. The recognition expert (an MLP classifier handling 7,425 character classes) associates a list of character candidates with recognition scores to each node of the graph. The interpretation expert generates linguistic meaning for the different paths in the segmentation graph, using a word tri-gram language model based on a 130K word lexicon to evaluate the linguistic likelihood of the interpretation of a given path of the graph. Moreover, a global discriminant training scheme on the text level with automatic learning of all classifier parameters and meta-parameters of the recognizer is employed. The three systems differ in the trade-offs between speed and recognition, the VO-1 is the fastest but slightly less accurate than the VO-3 which provides the highest accuracy. The VO-2 is a compromise between them.

IV. RECOGNITION RESULTS

The submitted systems were evaluated on the competition test datasets, and each system loads the test samples from hard disk and output the recognition results in a result file of specified format [26]. All systems were executed on a personal computer with Intel Core2-Duo-3.0GHz, 4G RAM, integrated graph card and MS Windows XP OS. For isolated character recognition, we also report the average processing time per character. For handwritten text recognition, we report the average time per text line. The number of characters per text line is about 26.68 (slightly different between online and offline data). As a measure of system complexity, we also show the size (number of bytes) of dictionary file, which stores the classifier parameters and context model parameters.

The evaluation results of isolated character recognition systems are listed in Table 2 (offline) and Table 3 (online), and the results of handwritten text recognition systems are listed in Table 4 (offline) and Table 5 (online), where the last column shows the dictionary size. Some systems are given the size of the executive file which embeds the dictionary.

Table 2. Results of offline character recognition.

System	CR (1)	CR (10)	Ave time	Dic size
CASIA-CREC-1	83.02%	97.15%	0.93ms	5.71M
CASIA-CERC-2	82.02%	96.75%	0.90ms	10.33M
CASIA-CERC-3	82.45%	96.97%	0.92ms	12.17M
CASIA-CSIS	90.77%	98.66%	12.25ms	457.23M
HKU	91.87%	98.99%	183.32ms	475.41M
IDSIAnn-1	92.05%	99.27%	86.21ms	27.35M
IDSIAnn-2	**92.18%**	**99.29%**	86.21ms	27.35M
SCUT-HCII	86.01%	93.44%	2.96ms	6.51M
THU	91.54%	98.91%	6.94ms	188.64M

Table 3. Results of online character recognition.

System	CR (1)	CR (10)	Ave time	Dic size
IDSIAnn-1	92.95%	99.38%	86.70ms	27.35M
IDSIAnn-2	93.06%	99.40%	86.70ms	27.35M
SCUT-IntSig-1	89.63%	96.55%	1.70ms	1.32M*
SCUT-IntSig-2	93.15%	97.84%	8.14ms	8.60M
THU	93.84%	99.27%	8.27ms	51.11M
VO-1	94.83%	99.41%	2.29ms	9.80M*
VO-2	95.68%	99.52%	6.29ms	26.94M*
VO-3	**95.77%**	**99.54%**	9.60ms	41.62M*
XD-IIPR	76.42%	89.61%	2.71ms	28.86M

Table 4. Results of offline text recognition.

	CR	AR	Ave time	Dic size
CASIA-CREC	74.06%	68.51%	0.30s	13.41M
SCUT-HCII	63.17%	62.05%	2.83s	10.56M
THU	**77.26%**	**70.63%**	0.84s	102.03M

Table 5. Results of online text recognition.

	CR	AR	Ave time	Dic size
SCUT-HCII	62.48%	58.50%	0.27s	4.41M
VO-1	92.36%	91.64%	1.02s	16.30M*
VO-2	93.79%	93.16%	1.35s	23.68M*
VO-3	**94.33%**	**93.56%**	2.41s	28.66M*

*Size of executive file embedding dictionary.

In offline character recognition, the system IDSIAnn-2 yields the highest accuracy and accumulated accuracy. The HKU and THU systems also yield comparable accuracies, but the THU system runs much faster. The superior performance of IDSIAnn is attributed to its complex neural network structure and discriminative training with large number of original samples and distorted samples. Both the HKU and THU systems use direction histogram features and quadratic discriminant classifiers. The HKU system also used distorted samples in training, while the THU system trained classifier discriminatively. On the other hand, the high speed of CASIA-CREC systems is attributed to its simple classifier structure and parallel computation technique. The SCUT-HCII system also has fairly low complexity.

In online character recognition, The VO-3 system yields the highest accuracy, leading with a large margin to the ones of other groups. The superior performance of VO systems is due to the fact that they use multiple features, train neural network classifier with large number of multi-source samples and distorted samples. Another neural network classifier, IDSIAnn, also performs fairly well even though converting digital ink to image without utilizing dynamic features. Among the systems using statistical classifiers, the THU system performs best. The SCUT-HCII systems show good tradeoff between performance and complexity. The inferior performance of the XD-IIPR system indicates that the implementation was not optimized.

The best results of both offline and online character recognition are much better than the best ones of Competition 2010 [2], where 89.99% of offline recognition and 92.39% of online recognition were achieved on the same test datasets as for 2011. Also, the best performing groups in 2010, HKU and SCUT-HCII, exhibited evident progress in 2011.

In offline text recognition, the system THU reports the highest CR and AR. All the three participating systems take the character over-segmentation strategy and integrate the character recognition model, linguistic and geometric contexts. The relatively low performance implies that all the systems need improvements in implementation.

In online text recognition, the systems of VO yield superior performance. They also adopt the character over-segmentation strategy, but implement the character classifier (neural network with discriminative training on large number of samples), context models, and combine the models with better implementation. Though the SCUT-HCCII system runs faster, its implementation needs optimization to improve the performance.

Overall, the results of isolated handwritten Chinese character recognition have shown evident progress compared to the previous results. The research of handwritten Chinese text recognition has not been widely undertaken, but the competition results are still encouraging. Particularly, the systems of VO have reported rather high recognition rates in online handwritten character recognition and text recognition.

V. CONCLUSION

The Chinese Handwriting Recognition Competition 2011 attracted eight groups to participate and received 25 systems for four tasks: offline isolated character recognition (Task 1), online isolated character recognition (Task 2), offline handwritten text recognition (Task 3), and online handwritten text recognition (Task 4). The best results were yielded by the systems of IDSIA (Task 1), VO (Task 2), THU (Task 3) and VO (Task 4), respectively. The submitted systems are variable in complexity in respect of dictionary size and processing time. We look forward to more participants in the future competitions and more researchers joining the research of Chinese handwriting recognition.

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