Handwriting Character Recognition as a Service：A New Handwriting Recognition System Based on Cloud Computing

Yan Gao, Lanwen Jin[+], Cong He, Guibin Zhou
School of Electronic and Information Engineering
South China University of Technology
Guangzhou, China
thegoldfishwang @163.com, +lianwen.jin@gmail.com

***Abstract*—In this paper, we propose a new framework of providing Handwritten Character Recognition as a Service (HCRaaS) via Internet, based on cloud computing technology. Using the proposed Cloud-based recognition platform, we would be able to apply many advanced algorithms in practice, such as modified quadratic discriminant function (MQDF) and SVM classifier used for large scale character recognition, writing adaptation technology, and handwriting Chinese word/textline recognition that usually involve large storage and computation cost. With the merits and characteristics of HCRaaS, users of different mobile devices are not only no longer subject to local computing capacity and storage resource constraints，but also, they can benefit from higher recognition accuracy and personalized service with low hardware costs. The experimental results show that, the proposed HCRaaS system based on Cloud computing can provide reliable handwriting solution across different mobile OS with higher recognition performance.**

Keywords-handwriting recognition; Cloud computing; HCRaaS

I. INTRODUCTION

Nowadays, personal hand-held devices, such as smart mobile phones, personal digital assistants (PDAs), e-book readers and Tablets (such as iPad), have been playing important roles in human's life. With the widespread use of touch screen and the rapid development of handwriting recognition technology, the handwriting input method is becoming more and more popular on mobile terminals. However, many advanced theoretical algorithms can't be directly applied to mobile terminals, because of the hardware performance limitation of mobile terminal and the high complexity and storage requirement of the algorithms. In order to perform handwriting recognition on mobile terminals, simpler classification methods or compressed classification models have to be applied to reduce the requirement for hardware, resulting in the cost of decreasing recognition accuracy.

For the above reasons, in this paper, we present a new handwriting recognition system based on Cloud computing, which provides an innovative network application model for the traditional handwriting input methods on mobile devices. Using Cloud-based method, many advanced theoretical algorithms can be applied to the handwriting recognition system, users no longer subject to local computing capacity and storage resource constraints. The mobile devices can be made into much smaller size, lighter weight, but has higher accurate recognition rate and personalized service. Besides, Cloud computing platform differentiate from the traditional C/S model and has its own advantages: Cloud computing offers the same super computer services over the Internet and dynamically allocates distributed computing resources; The Cloud server can easily handle service requests of multiple concurrent users simultaneously; Cloud computing system supports cross-platform client terminals[12-14]. Therefore, it would be more convenient and easier for mobile devices with different operation systems to use latest handwriting technologies. With the proposed new framework of regarding Handwritten Character Recognition as a Service (HCRaaS), we implement handwriting recognition system based on Cloud computing, and applies several algorithms to this system, including uncompressed MQDF classifier and writing adaptive technology. Experimental results show that, the proposed HCRaaS system can provide reliable handwriting recognition service across different mobile OS with higher recognition performance

The rest of this paper is organized as follows: Section II presents some typical handwriting recognition algorithms we used in our HCRaaS system, and studies on the computing complexity and storage of these algorithms. The Cloud-based recognition system.is presented in Section III. Section IV gives the experimental results on the proposed system and traditional system for comparison. Finally, conclusions are summarized in Section V.

II. HANDWRITTEN CHARCTER RECOGNITION TECHNOLOGIES

The general steps of handwriting recognition include preprocessing, feature extraction, classification and so on. The preprocessing technology consists of binarization, normalization, sampling, smoothing and denoising. The widely used feature extraction methods for handwritten Chinese character recognition include 8-directional feature extraction [1] and Gradient feature extraction [2] etc. In classification step, minimum Euclidean distance classifier and MQDF classifier are mainly used. They [3-5] have performed well in handwriting recognition. The recognition rate of single regular-writing character recognition has reached 98% to 99%. However, due to the diversity of user writing style and the limitation of the training data in real

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world, the recognition rate is not so high. For example, In Chinese Handwritten Recognition Contest 2010 [15], the highest recognition rate for unconstrained cursive online handwritten Chinese recognition is only 92.39%.

A. MQDF classifier

MQDF classifier proposed by Kimura et al. [6] is widely used in handwriting recognition and its good classification performance improves the recognition rate significantly. Based on Bayesian decision rule, the quadratic discriminant function (QDF) is obtained under the assumption of multivariate Gaussian density for each class. The MQDF is obtained by making a modification to the QDF with K-L transformation and smoothing the minor eigenvalues, which is shown in Formula (1).

$$g_1(x,\omega_i)=\frac{1}{\delta_i}\left\{\left\|x-\bar{x}_i\right\|^2-\sum_{j=1}^{K}(1-\frac{\delta_i}{\lambda_{ij}})[\phi_{ij}^T(x-\bar{x}_i)]^2\right\} + \sum_{j=1}^{K}\log\lambda_{ij}+(D-K)\log\delta_i \quad (1)$$

where $\bar{x}_i$ denotes the mean vector of class ω_i; λ_{ij} and ϕ_{ij} denote the eigenvalues and eigenvectors respectively of the covariance matrix of class ω_i; D is the dimension of $\bar{x}_i$; K is the number of dominant eigenvectors and δ_i is a constant.

The MQDF classifier needs to train and store the dominant eigenvalues and eigenvectors of the covariance matrix of each class. The storage problem mainly comes from the eigenvectors of each class. If class number is 3755, feature dimension is 512, dominant eigenvector number is 25, when 4-byte floating number is used, the storage is 3755 × 512 × 25 × 4 bytes, about 183 MB. Although the dimension *D* of the feature vectors can be reduced by linear discriminant analysis (LDA) [11], the eigenvectors still need about 57MB storage after the dimension is reduced to 160. The storage of MQDF is huge and it is very critical for the mainstream PDA and Pocket PC to use the MQDF classifier directly because their memory space is usually equal or less than 64MB.

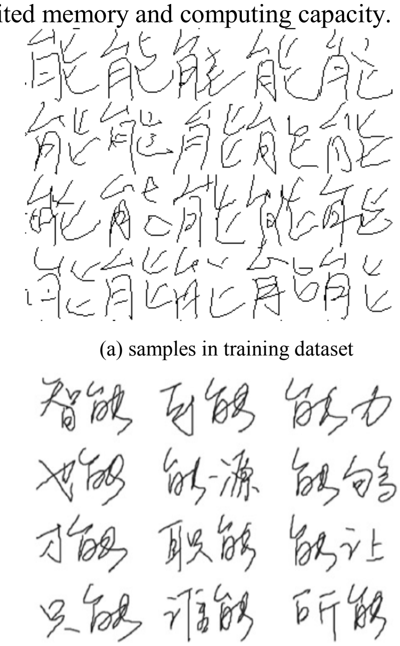
T. Long et al. [7] propose a method of building a compact MQDF classifier by subspace distribution sharing to form a codebook for the subspaces of the MQDF. By this method the storage of MQDF can be compressed from 57MB to 3.58MB. Furthermore, a two-level Euclidean distance classifier can be employed to accelerate the recognition process. Fast recognition speed and compact dictionary size make the MQDF classifier be practical for hand-held devices. However, the cost of all these methods is the reduction of recognition rate.

B. Writing Adaptation

Due to the limit samples of the handwriting dataset for training, it can't cover all the writing styles of all writers, the recognition rate may not be so high for some writers in practice. As shown in Figure 1, Figure 1(a) shows the character "能" in training dataset, Figure 1(b) shows "能" written by a certain user. It is obvious that the recognition rate will be very low when the training dataset covers no such writing style of character "能".

Therefore, K. Ding et al. [8] proposed a new writer adaptation method based on incremental LDA and incremental MQDF. This method updates the classification parameters to improve the user's recognition performance according to the samples written in his/her own style. This writing adaptive technology provide users with a personalized service, it improves the recognition rate for the user without reducing the recognition rate for the others.

However, writing adaptation technology needs to save the users writing samples, meanwhile updating the classifier parameters need a lot of computation. So it is not practical for applying writing adaptation in mobile terminals which has limited memory and computing capacity.



(a) samples in training dataset

(b) samples written by users

Figure 1. Character "能" in SCUT-COUCH database [10] written by different users

III. CLOUD-BASED RECOGNITION SYSTEM

The architecture of the proposed Cloud-based handwriting recognition system is shown in Figure 2. The client terminal is a mobile phone with Android platform or could be other hand-held devices with different operating systems, such as Windows mobile, Symbian, Mac OS x, Embedded Linux, Rim, iOS and so on. There is a handwriting panel which can record the input strokes. The client terminals on several platforms are shown in Figure 3. The server is virtual Cloud infrastructure based on Enomalism [9] combining many physical server machines and personal computers. When finishing writing, strokes are sent to the server by socket protocol through WiFi, GPRS, EDGE or the 3G networks. The handwriting recognition are run on the Cloud server. Relative to the bandwidths of the above networks, the data of the strokes and candidates is small, so it costs very little transmission time and users have no sense about the delay. It feels like that the recognition is done locally. Considering the situation that no network is available, we also embedded a minimum distance classifier into the Android mobile phone.

In theory, the memory and computing capacity of Cloud server are infinite[1]. So, we can implement any state-of-the-art recognition algorithm to get very high accuracy in real-time. In this paper, the uncompressed MQDF classifier and writing adaptation technology are applied in the proposed Cloud handwriting recognition system, and these algorithms work very well in our HCRaaS system.

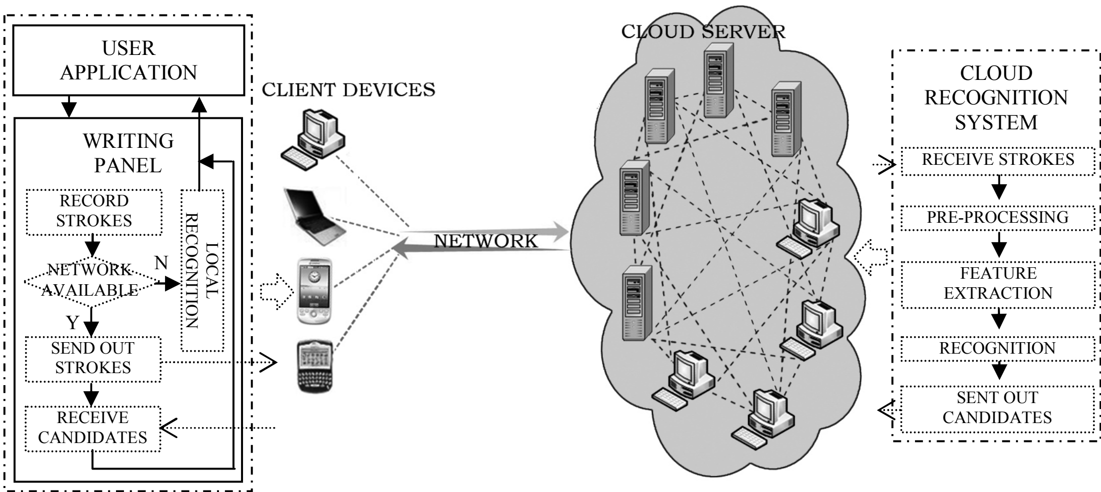
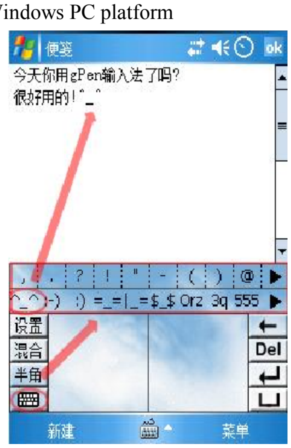


Figure 2. Framework of the proposed HCRaaS system based on Cloud computing

(a) Client terminal on Windows PC platform

(b) Client terminal on Android platform



(c) Client terminal on Windows Mobile platform

Figure 3. Client terminals on different platforms

IV. Experiments and Analysis

The dataset used in this paper is SCUT-COUCH2009 [10], which is a comprehensive dataset that consists of 11 subsets, including Chinese characters, words, pinyins, letters, digits, symbols and so on. SCUT-COUCH2009 is collected with PDA (Personal Digit Assistant) and smart phones with touch screens, contributed by more than 190 different persons, resulting in more than 3.6 million handwritten samples.

We evaluate the performance of the proposed Cloud handwriting recognition system from classifier storage, stability, recognition rate and computation cost. The uncompressed MQDF classifier is applied in Cloud recognition system, while the traditional compact version is applied at mobile terminals.

The comparison of recognition rate is shown in Table I. The recognition subsets include Chinese characters, digits, letters and symbols. It is obvious that the recognition rate of Cloud-based HCRaaS system is much higher than traditional system. Although the storage of the classifier is larger, it is acceptable to the Cloud server with huge storage. For the traditional system, classifier is compressed to be used on smart phones and Pocket PC, at the cost of reducing accuracy rate.

Table II shows the comparison of recognition time. The transmission time of HCRaaS Cloud system is fast. With powerful calculating capacity of Cloud server, the total recognition of HCRaaS Cloud system speed is also faster.

TABLE I. COMPARISON OF RECOGNITION RATE

System	Storage	Recognition rate (%)				
		Digit	Letter	Symbol	CHS	Avg.
HCRaaS Cloud System	30MB	99.0	96.11	93.68	96.05	96.17
Traditional System	2MB	98.2	94.87	91.20	93.37	93.38

TABLE II. COMPARISON OF RECOGNITION RATE

System	time			
	Feature extraction	classify	network transmission	total
Cloud System	1.5ms	3ms	25ms	29.5ms
Traditional System	15ms	25ms		40ms

TABLE III. WRITING ADAPTATION ON CLOUD SYSTEM

users	Sample number	Sample storage	Adaptation time	Rate before adaptation	Rate after adaptation
1	15,000	7.78MB	25Min	94.29	96.51
2	15,000	6.94MB	23Min	95.92	98.27
3	15,000	9.39MB	26Min	88.86	94.77
4	15,000	7.19MB	25Min	90.96	97.97
5	15,000	7.57MB	25Min	92.67	96.38

The third experiment we carried out aims to verify the feasibility of writing adaptation applied on HCRaaS Cloud system. As shown in Table III, after writing adaptation, the recognition rate has been improved significantly. Although writing adaptation need to store samples written by users, there is no problem for the Cloud server with huge storage space. Writing adaptation is run in the background of Cloud server, so it will not affect users. As shown in Table III, after writing adaptation, the recognition rate has been improved significantly.

Some more experiments are designed to verify the overall performance of the HCRaaS Cloud server when multiple concurrent users are connecting to the server. The experiment simulates multiple users to access the server simultaneously, and then record the related performance indexs. Table IV shows the performance of the HCRaaS system when multiple users access the Cloud server simultaneously against performance of traditional server. From Table IV, we can see that the access *rate* of HCRaaS Cloud server is 100%, the processing time for most users is short. However, for the traditional server, the upper bound concurrent access number is 300, and with the increase of the concurrent users, the access time increased substantially, and the access rate dropped significantly. This shows that the HCRaaS Cloud server can better process the concurrent access of multiple users so as to improve the computation capacity available to concurrent users effectively.

Figure 3 shows the average processing time when multiple users access HCRaaS Cloud server. There are four curves corresponding when 100, 300, 500 and 1000 concurrent users respectively. These curves are smoothing, showing that the Cloud server has good stability and ensures the reliability to obtain the service when mobile terminals access HCRaaS system via network.

TABLE IV. COMPARISON OF CLOUF SEVER AND TRADITIONAL SERVER

Server model	number of concurrent users	100	300	500	1000
Cloud server	**Actual number of concurrent users**	100	300	500	1000
	average processing time (s)	0.014	0.016	0.019	0.025
	processing time of 90% users(s)	0.023	0.023	0.032	0.043
	average throughput (bytes/s)	5811	7003	7334	7706
Traditional server	**Actual number of concurrent users**	100	248	—	—
	average processing time (s)	0.041	0.34	—	—
	processing time of 90% users(s)	0.123	0.635	—	—
	average throughput (bytes/s)	1604	1124	—	—

Figure 4. average processing time when multiple users access Cloud server

V. CONCLUSION

In this paper, we propose a new handwriting recognition system, HCRaaS, based on Cloud computing.. We have already implemented some state-of-the-art handwritten Chinese character recognition technologies, such as MQDF classifier and writing adaptation technology, in the proposed HCRaaS Cloud system. Experiments are carried out to verify the reliability and performance of the Cloud-based recognition system. The main advantages of Cloud based HCRaaS system include: (1) recognition *accuracy* is no longer constrained by the hardware resources of mobile terminals and can reach a higher level; (2) the computation and storage requirement of client terminals is low; (3) Classifier can be upgrade on the server and users can benefit the new state-of-the-art recognition technologies without update their devices.

We hope that with the idea of regarding handwritten character recognition as a service based on Cloud computing, it can be more convenient and easier for mobile devices with different operation systems to use and benefit from latest advance handwriting technologies.

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