A Survey on the Classifiers in On-line Handwritten Uyghur Character Recognition System

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Abstract

With the fast development of information technology made people eager to get access the convenient implementations of modern technology in every walk of life. Online handwritten recognition technology for Uyghur is also receiving great need, too. Precious work form researchers for this technology has been gifted many gains. This paper observe the classifiers used in previous work on this field in order to see their adaptabilities for Uyghur online handwritten recognition, and acquire clues for classifier implementation in future work.

Keywords: Uyghur, on-line handwritten recognition, classification, classifier

1. Handwritten Recognition Technology and its Significance

The emerging of first printing technology made the human thoughts and history capable for saving and transmitting generation after generation, and sometimes with world-wide effect. After the passing through the industrial revolution, Electrical revolution, Atomic age, human-kind entered into our Information era. The surprising speed of electronic processing and popularization of Internet made the information already globalized for many areas. This fast developing age is putting big threat for many ethnic groups' language, culture and existence, meanwhile providing great opportunities to express and strengthen themselves via sharing the most updated information and technologies. So, millions of books in dark and dusty corners of old libraries are becoming digitized in order to get access to read by computers and transmit by Internet. Everyone can see the huge workload and time cost that this task requires and automatic word recognition tool is a must. Optical Character recognition System, abbreviated as OCR, handled this problem out in a great extent, and we see unending materials in electronic library with quite easy access. After the recognition of printed letters, the next step should be the recognition of handwritten scripts. However, this is a obstacle technology from the very beginning [1]. Everyone has unique handwriting style, and handwriting style of a same one is also influenced by many factors during the actual writing. In addition to that, people always break the standard writing rules. Urgent need for modern communication made the online handwritten technology a necessary. After the great success of Chinese online handwritten technology, minority groups in China also started their endeavor for their own scriptures including Uyghur. As a main language in north-western region of China and central Asia, also holding tight linguistic bonds with many languages in Turkish family of Altaic language system, the study on Uyghur online handwritten recognition technology has significant research value.

2. Uyghur Online Handwritten Recognition System

The research and experiments conducted on Uyghur online handwritten recognition can be summarized as the framework shown in Figure 1



Figure 1. Block Diagram of Uyghur on-line Handwritten Character Recognition System

As shown in Figure 1, collecting handwritten samples always is the priority task, for any idea or method can't be tested without experiment and any experiment can't be run without samples. In online handwritten recognition, the content of sample data used to be the two-dimensional coordinate of the position which touched on the notepad screen or the sensitive surface of intelligent device. Also, the time order of coordinates of touched positions are recorded during handwriting. Usually, the first hand handwritten samples are written in various ways in size, angle and screen's blocks, which means some people write into a corner instead of the center of screen. Therefore, a pre-processing operation should be done before these samples go into the later stages of recognition. Normalization and noise elimination are the basic components in pre-processing stage [2]. The all samples receive the feature extraction process which is vital for recognition accuracy and system efficiency. Some distinctive characteristics of samples are chosen to represent a kind of character or a word. The distinctive characteristics of a category or class are called feature. Features can be observed usually in three ways: structural properties of the object and the statistical characteristics or a hybrid application of those two methods [3]. Some part of collected samples are participated in training process which aims to build model for characters or in more generally speaking, to build models for recognition categories. Sometimes, a few alternative models are built for one single character or category considering the reluctance and randomness of handwriting. In recognition experiment, the untrained samples are expected to go through the identification test. The classification techniques in training and testing units are same in method and parameters. The recognition criteria such as accuracy, recall rate, precision etc are obtained from the identification process.

3. The Classifiers used for Uyghur Handwritten Recognition

This paper observed the classifier applied or proposed in Uyghur online handwritten recognition technology until the recent days. Some scenarios from off-line printed or handwritten recognition are taken into observation for reference, too. Table 1 gives some information of the classifiers or classification techniques used in Uyghur handwritten recognition.

Ref No.	Classifier / Training algorithm	Distance Measure	Data-set Size	Accuracy
4	Minimum Distance Classifier	Minkowsky Distance	NG (Not Given)	NG
5	(MQDF) Modified Quadratic Discriminat Function		48800 samples for test	99.48%
6	Template Matching		NG	>98%
7	Piecewise Linear Sorter	Euclidean Distance	NG	>90%
8	Artificial Neural Networks		10 different users	91%
9	Artificial Neural Networks (BP with Gradient Descent)		230 samples for training	98.21%
10	Nearest Neighbor Classifier		10 different handwriters	NG
11	Minimum Distance Classifier	Euclidean Distance	465 samples	>86%
12	Minimum Distance Classifier	Weighted Euclidean & Chi-square Distance combined	handwritten samples from Chinese, English, Uyghur, Tibetan	>92%
13	BP and HMM (Freeman code) combined method		26617samples for mathematical formula, 400 samples for test	91.75%
14	BP		480	96.46%
15	SVMwith Gradient Descent		400×128=51200 samples	>90%
16	Template Matching with XOR operation		400 samples for test	97%
17	Minimum Distance Classifier	Weighted Euclidean Distance.	$6 \times 100=600$ samples 400 for training , 200 for testing	89%
18	Minimum Distance Classifier	Euclidean Distance,	70 groups for training, 45 groups for testing,	75%
19	Minimum Distance Classifier	Euclidean Distance	$400 \times 128=51200$ samples, 50% trained, 50% tested	
20	НММ		2000 samples , 90% for training, tested on five different fonts of Uyghur typed letters,	
21	SVM with RBF kernel Surpassed MQDF, DLQDF, LVQ (modified quadratic discriminant function, the discriminative learning quadratic discriminant function, the learning vector quantization classifier)		400×128 =51200 samples, 70% trained, 30% tested	89.08%
22	SVM		32* 50 for training, 32*100 for testing,	93%
23	Minimum Distance Classifier	Euclidean Distance & Manhattan Distance	120 users	NG
24	Combined classifiers using KNN	DTW with Euclidean Distance	51200 samples	
25	Weighted Naïve Bayes		102×128=13056samples, 60 groups for training, 42 groups for testing	93.15%
26	KNN	Chi-square distance	1000 signatures	98.5%.
27	KNN	Euclidean distance,	115 group of samples, 75groups for training. 40 groups for testing	95%
28	Classifier Combination Using Nearest Neighbours, MST and DTW clustering	Euclidean Distance	51200 samples	89%
29	Minimum Distance Classifier	Euclidean Distance	12800 samples, 280 groups for training, 120 groups for testing	78%

Table 1. Classifiers and Data Sets used for Uyghur Handwritten Recognition

Ref No.	Classifier / Training algorithm	Distance Measure	Data-set Size	Accuracy
30	Semi-supervised K-means clustering		Samples from IFN/INET2.0 Arabic Storehouse and self-collected 160 ones	
31	Minimum Distance Classifier	Euclidean distance	12800 and 51200 samples, 80% for training, 20% for testing	94.50%
32	Minimum Distance Classifier	Euclidean distance	12800 and 51200 samples, 80% for training, 20% for testing	98.77%
33	Combination of Gaussian Mixture Model and Hidden Markov Model			99%
34	HMM and Statistical Language Model		24 000 Uyghur words, 759 Arabic words	97.45%, 85.80%

With a quick glance to Table 1, it is very clear to see that the sample data library for many of the experiments are not from one source and some of them are even not addressed. In addition to that, the samples are different in volume. This situation makes us unable to compare the recognition results and inconvenient to analyze the performance of different classifiers.

From Table 1, it is not difficult to find that see that minimum distance classifier has been a hot attractive point for its simple nature in theory and application. Some classic or popular classifiers including HMM, SVM, NB have shown themselves in seldom appearance. The new developing technologies such as artificial neural networks also have been tested with the application of BP, mostly. Ensemble application of different classifiers appeared in most recent work and produced the highest classification or recognition rate in experiment.

4. Popular Classifiers

From Table 1, we can easily see that many of the popular classical classifiers have not been applied yet [35, 36], except SVM, HMM, BP, NB etc. perhaps this is due to the lacking of research staff on Uyghur handwritten recognition and for some other reasons. However, applied classification methods and the obtained recognition results using them do not necessarily mean that they are the ones which most fit for Uyghur handwritten recognition. So, there are lots of work has to be done for classification study and its application on Uyghur handwritten recognition. In this section, some popular classifiers with their advantages as well as shortcomings are introduced [37~40].

• **RF--Random Forests**

Random Forests are showing thenselves as very successful ensemble learning method for classificationegression and other tasks, which are integrated form multiple decision trees. The easily overfitting problem is beaten in Random Forests. Random forests found themselves as good solver for lots of classification problems. For their distinct advantages of being fast and scalable and convenient for tuning multiple parameters simultaneously, Random Forests are earning quite popularity in these days.

• SVM—Support Vector Machines

SVMs are the most popular and most successful learning algorithm for classification tasks and regression analysis, nowadays. High accuracy, nice theoretical guarantees regarding over fitting and with an appropriate kernel they can handle well the linearly inseparable data in base feature space. SVMs are especially popular in text classification problems where very high-dimensional feature spaces have to be worked on. Disadvantages: SVMs are mostly Memory-intensive, hard to interpret and kind of annoying to run and tune. They are very much relied on adequate choosing of kernel methods; in addition to that, there is no generalized solution for kernel choosing. SVMs sensitive for missed data, quite dependent of the feature set size and take a considerable amount of time to train, this leads to decrease the interactive efficiency.

• NB--Naive Bayes

Naive Bayes is a popular algorithm in the family of simple probabilistic classifiers. The Bayes theorem with strong independence assumptions between data features are the main theoretical base of naïve Bayes classifiers. It has a property of simplicity in mathematical foundation and training computation and quick to execution. Stable classification results are the main advantage of Naïve Bayes algorithm. The classification performance is not much influenced by missed data and small size of parameters can meet the requirements. However, Naïve Bayes classifiers lose performance on big data, and most notably, they can't learn interactions between data features. Niave bayes is not powerful enough to create accurate models on large data.

• KNN—K Nearest Neigbours

k-NN is one of the most popular and simplest, non-parametric learning algorithm used for classification and regression problems. It is a typical instance-based, lazy learning algorithm, where the function is only approximated locally and all computation is deferred until classification. KNN has advantages of being pretty easy and convenient for real world applications. When training data size is becoming larger, the KNN shows its power and effectiveness, but with the high cost of computational time consuming. As a Lazy Learning algorithm, KNN almost does not learn anything and classification is influenced by un-equally prepared volume of sample data.

• Logistic Regression

Logistic regression can be seen as a special case of generalized linear model. It measures the relationship between the categorical dependent variable and one or more independent variables by estimating probabilities using a logistic function. Logistic Regression has nice probabilistic interpretation and is not influenced by the correlation relationship of data features. The trained model can be easily updated to take in new data. It is a very reasonable alternative for a probabilistic dynamic framework that the new received data can be quickly incorporated to update the model in time.

• DT--Decision Trees

One of the most easily applied predictive modeling approaches, Decision Trees have

Advantages of being easy to interpret and explain, can easily handle the interactions between the features of data. Decision Tree methods are non-parametric, so they are not influence by whether data is linearly separable. However, DTs easily over fit and neglect some feature interactions very often. They are sensitive for missed data and features generated from insufficient data volume. They don't support online learning, so new tree has to be built when new examples come on.

• ANN--Artificial Neural Networks

Artificial neural networks are generally presented as systems of interconnected neurons which exchange messages between each other. The tunable weighted connections between neurons make artificial neural networks' adaptive to inputs and capable of selflearning. Distributed processing and noise protective mechanism, High classification accuracy, powerful online memorizing and learning ability make artificial neural International Journal of Hybrid Information Technology Vol.9, No.3 (2016)

networks quite applicable for complex nonlinear problems and tasks that are hard to solve using ordinary rule-based algorithms. Sometimes, it is hard to adapt neural networks. Because they require large volume of parameters, can't observe the learning process, results are difficult to explain and take as granted. Most considerably, the learning time is too long that neural networks sometimes even can't learn.

• Genetic Algorithm

Genetic algorithms belong to the larger class of evolutionary algorithms (EA), which generate solutions to optimization problems using techniques inspired by natural evolution. Genetic algorithms have strong stochastic searching ability and advisable for ensemble application. Beginners perhaps find Genetic algorithms inconvenient for programming. They often show low accuracy when they are applied alone.

Adaboost

Adaboost is a kind of classifier with high precision. It provides the framework for classification and makes the establishing of sub-classifiers very easy. It is simple in foundation and does not need feature selection. You don't worry about over fitting problem.

• HMM

A HMM can be presented as the simplest dynamic Bayesian network. HMM is applicable for more complex data structures and the modeling of non-stationary data.

In fact, Hundreds of classifiers are being used in different fields. We would like to recommend a few more classifiers from different categories of classification algorithms [41].

- 1. Elm_kernel_m from Artificial Neural Networks
- 2. C5.0_t from Boosting algorithms
- 3. fda.t from Discrimnant Analysis
- 4. RandomCommittee_w from ensemble classifiers
- 5. Multinom_t from Logistic and Multinomial Regression algorithms
- 6. gcvEarth_t Multivariate adaptive regression splines
- 7. glmnet_R from Generalized Linear Models
- 8. treebag_t From Bagging Algorithms
- 9. RandomSubSpace_w from Decision Tree algorithms
- 10. C5.0Rules_t from Rule based methods

5. Recommendations

We believe the following recommendations will be helpful for the advancement of Uyghur handwritten recognition.

First of all, it is strongly recommended that an authorized handwritten sample library with enough volume has to be established, so that each one can use it freely and compare the performance of different classifiers and new methods. An open data source does provide a great forum of learning each other and prevent the redoing of some work.

Second, different classifiers should be comparatively tested, instead of putting just one kind of classifier on experiment. A good classifier in common does not necessarily will be the best one for all scenarios. Perhaps, some data structures or features require the quite sophisticated classification methods with time- costing, while some data structures need to be processed with handy and quick classifiers. Some classifiers may give better accuracy, but produce low efficiency of whole system due to lazy learning and slow solving nature. In contrast, although some classifiers can't make competent classification accuracy, the speed from their application makes the user more satisfactory.

Thirdly, proposing new kinds of classification methods or the adapted modification of classic classifiers are very much hoped. The natural languages are very complicated that they are uttered obeying to natural rules and language holder's subjective influences such as thought, ambition, temper and emotion. So, the classifier that simply used on the natural or mechanical stochastic data may will not perform as good as usual. The different characteristics of natural language data should be studied and appropriate classification methods are applied. It is hopeful that classic classifiers can be adopted with special modifications, too.

Then, the ensemble application of classifiers should be studied for a successful application of integrated classifiers can meet acceptable accuracy as well as the satisfied speed [42]. It is possible that data structure from natural languages like handwritten samples can be observed in different angles to find their static or dynamic, simple or complicated, structural or statistical, surface layer or deep-in characteristics. When appropriate classifiers are applied for each part or feature of data, the classification accuracy and overall system efficiency can be improved greatly. However, this is dependent on careful studying both of data structure the classifier attributes.

6. Conclusion

The great need for new communication technologies and intelligent applications require handwritten recognition technology to have high accuracy and acceptable speed. Studies on Uyghur handwritten recognition have been gifted with many achievements, too. Still, lots of work is open for researchers for better improve the accuracy and efficiency standards of both online and offline implementations of Uyghur handwritten recognition. This paper examined the classification methods applied in Uyghur handwritten recognition and the sample data sources the classifiers run on. Although, the sample data sources with different size and standards make the comparing of classifier performances impossible, many advances in classifier application have been obtained. A brief introduction of popular classifiers and a few recommendations for applying them in more advanced ways are given, and this can be the main content of future work on Uyghur handwritten recognition.

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