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A Survey on Handwritten Devnagari Character Recognition Methods

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Abstract—Nowadays character recognition has gained lot of attention in the field of pattern recognition due to its application in various fields. Optical Character Recognition (OCR) and Handwritten Character Recognition (HCR) has specific domain to apply. OCR system is most suitable for the applications like multi choice examinations, printed postal address resolution etc. While application of HCR is wider compare to OCR. HCR is useful in cheque processing in banks; almost all kind of form processing systems, handwritten postal address resolution and many more. In coming days, character recognition system might serve as a key factor to create paperless environment by digitizing and processing existing paper documents. In this paper, we have provided the detail study on existing methods for handwritten character recognition. Classification methods based on learning from examples have been widely applied to character recognition from the 1990s and have brought forth significant improvements of recognition accuracies. This class of methods includes statistical methods, artificial neural networks, support vector machines, multiple classifier combination, etc. In this paper, we discuss the characteristics of the classification methods that have been successfully applied to character recognition, and show the remaining problems that can be potentially solved by learning methods.

Keywords—OCR, HCR, Features, Training, classification.

I. INTRODUCTION

Handwriting recognition is described as the ability of a computer to translate human writing into text. This can be achieved by two ways, the first of these handwriting recognition techniques, known as optical character recognition (OCR), is the most successful. OCR is also used to convert large quantities of handwritten documents into searchable, easily-accessible digital forms. The second technique of handwriting recognition, often referred to as on-line recognition. Methods and recognition rates depend on the number of constraints on handwriting. The constraints are mainly characterized by the types of handwriting, the number of writers, the size of the dataset and the spatial layout. From past many years, many academic laboratories and companies are involved in research on handwriting recognition. The increase in accuracy of handwriting processing results from a combination of several elements i.e. the use of complex systems integrating several kinds of information, the choice of relevant application domains, and new technologies such as high quality high speed scanners and inexpensive powerful CPUs. In Character recognition system we required two things i.e. preprocessing on data set and decision making algorithms. We can categories preprocessing into three categories: the use of global transforms, local comparison and geometrical or topological characteristics. There are various kinds of decision methods have been used such as: various statistical methods, neural networks, structural matching and stochastic processing. Many recent methods developed by combining several techniques existing together in order to provide a better reliability to compensate the great variability of handwriting.

In the early stage of OCR (optical character recognition) development, template matching based recognition techniques were used [16]. The templates or prototypes in these early methods were designed artificially, selected or averaged from few samples. As the number of samples increased, this simple design methodology, became insufficient to accommodate the shape variability of samples, and so, are not able to yield high recognition accuracies. To take full advantage of large volume of sample data, the character recognition community has turned attention to classification methods based on learning from examples strategy, especially based on artificial neural networks (ANNs) from the late 1980s and the 1990s. New learning methods, using support vector machines (SVMs), are now actively studied and applied in pattern recognition problems.

Learning methods have beneficiated character recognition methods tremendously. They relieve us from painful job of template selection and tuning, and the recognition accuracies get improved significantly because of learning from large sample data. Some excellent results have been reported [17, 18, 19]. Despite the improvements, the problem is far from being solved.The recognition accuracies of either machine-printed characters on degraded document image or freely handwritten characters are still insufficient.The recent spurt in the advancement in handwriting recognition has provided publications but do not involve the performance comparison of artificial neural networks and support vector machines on the same feature set for handwritten Devnagari characters. In this paper, we discuss the results of ANNs and SVM applied on handwritten Devnagari Characters. The strengths and weaknesses of these classification methods will also be discussed.

II. DEVANAGARI SCRIPT AND DATASET

Devanagari alphabets are used to write Indian languages, including Sanskrit, Hindi, Marathi, Kashmiri, Sindhi, Bihari, Bhili, Konkani, Bhojpuri and Nepali from Nepal. Devanagari emerged around 1200 AD out of the Siddham script. It is immediate descendants of the Gupta script, ultimately deriving from the Brahmi script attested from the 3rd century BC. The descendants of Brahmi form the Brahmic family, including the national

alphabets of many other Indian languages.Devanagari is written from left to right along a horizontal line. Its basic set of symbols consists of 34 consonants or ('vyanjan') and 18 vowels ('svar'). Characters are joined by a horizontal bar that creates an imaginary line by which Devanagari text is suspended, and no spaces are used between words. Devanagari also has a native set of symbols for numerals. Devanagari owes its complexity to its rich set of conjuncts. A syllable ("akshar") is formed by a vowel alone or any combination of consonants with a vowel. Optical Character Recognition for Devanagari is highly complex due to its rich set of conjuncts. There are about 280 compound characters in Devanagari [22]. Due to the lack of uniform data sets for Devanagari script OCR there is very little research is going on. A best survey report on research in Devanagari is given[1,22].We have implemented different classifiers and taken the results so that it may be the bench mark for future research. In the present work we have developed handwritten database. For handwritten we have collect data from people of different age groups and from different profession. We have visited primary school,secondary school, High School, Government offices, Adult Education Night School for collecting data. This data were scanned at 300 dpi using a HP flatbed scanner and stored as gray-level images. The preprocessing

steps performed in this work are steps for rectification of distorted images, improving the quality of images for ensuring better quality edges in the subsequent edge determination step and size normalization.

The Hindi language consists of 49 characters (13 vowels, 36 consonants) and is written from left to right. A set of handwritten Hindi characters is shown in Fig.1

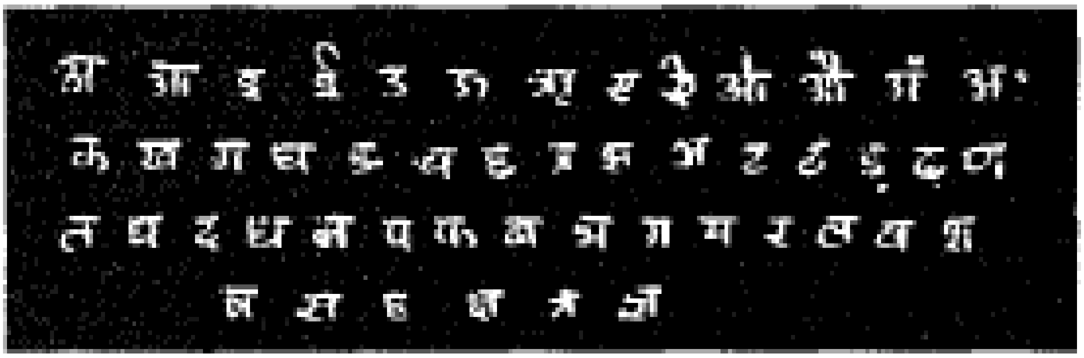

Fig.1 A set of handwritten Hindi characters

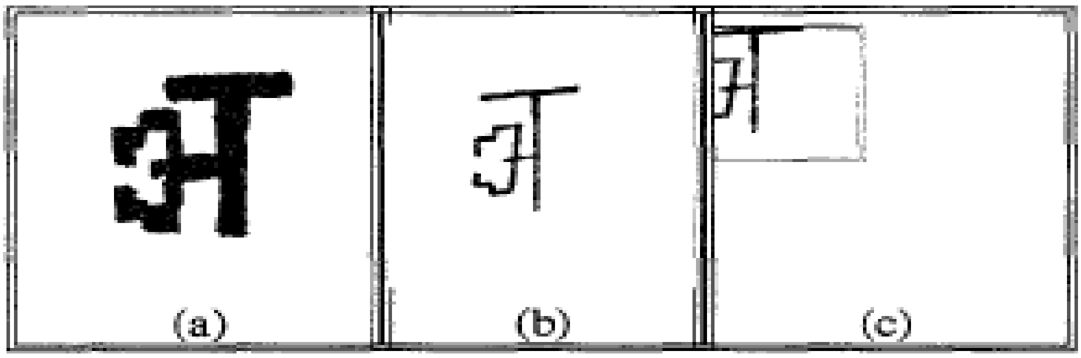

Fig.2 Skeletonization and normalization of a Hindi character.

III. CLASSIFICATION

A. Multilayer Perceptron(MLP)

Multilayer feed forward neural network with error back propagation is the widely used classifier for hand-printed problems and it performs better as compared to many other classifiers [3]. In error back-propagation algorithm, the gradient-descent method is generally used to minimize the squared error cost function. The resilient propagation algorithm has been contributed by Riedmiller et al[31] to overcome the shortcomings of gradient descent method in which the size of change in weights, say Δw_{jk}, depends upon the learning rate η as well as onpartial derivatives

$\partial E/\partial w_{jk}$ of the error surface. The unforeseeable behavior of partial derivative blurs the adapted learning rate η in gradient descent. Resilient propagation changes the size of weight update Δw_{jk} directly without considering the size of partial derivative. The resilient propagation has been used for conducting experiments here. In our experiments we have used implementation of resilient propagation algorithm available in [5].

B. Support Vector Machine (SVM)

The foundation of support vector machine is due to Vapnik [2] and its formulation is based on structural risk minimization (SRM) rather than empirical risk minimization (ERM). It is based on the concept of decision planes that defines decision boundaries. The decision plane is generally a hyper plane, which constitutes a line like function. SVM classifier will classify new training example say, u, as

$$g(\mathrm{u}) = \mathrm{sign} \sum_{i=0}^{Us} (\lambda\mathrm{idi}\ \mathrm{K}(\mathrm{u}, \mathrm{ui}) + \mathrm{c})$$

The value of parameters λi and c are maximizing and di is label of ui .

IV. PERFORMANCE COMPARISON

The experiments are conducted with various features as suggested for each stage as mentioned. Prior to perform recognition, the head line from each character is removed using a line removal algorithm which is beyond the scope of this paper. A character is size normalized to 32 ×32 after line removal using aspect ratio preservation method studied by Liu et al [18]. Since our database consists of more than 600 characters per class, the characters of each class are numbered. For our experiments we have used 600 characters per class from each class (alphabet character). In order to cross validate the results we have partitioned our database into four subsets: A, B, C and D. The size of each subset is equal. In each trial, 75% data is used for training and 25% data is used for testing, i.e. one subset is used to test and three subsets are used to train the classifier. Meaning thereby, four fold cross validation has been used. The experimental results for various stages with two classifiers are as:

a). The experimental results with MLP and SVM for primary stage classification are given in Table 1. Average classification accuracy means average accuracy (%) due to all the four sets / trials. Average primary classification time mentioned in Table 8 do not includes the feature extraction time. For primary classification, the GrdPsfs-142 feature set is dominating in respect of classification accuracy for both classifiers. The classification accuracy with SVM is 0.5 % large as compared to the classification accuracy with MLP. But classification time with SVM is about 6.2 times as compared to MLP. The classification accuracy of TdistPsfs-142 and NpwPsfs-142 features are 98.7% and 98.2%, respectively with SVM classifier, which are more than 0.5% less as compared to GrdPsfs-142 feature type with SVM. The classification error obtained using various features with MLP classifier is greater than 0.5% as compared to GrdPsfs-142 feature type with SVM classifier. The primary classification plays an important role. If a character is erroneously classified in first stage, this error is unrecoverable. The error must be reduced at this stage within reasonable classification time. So, it is suggested to use GrdPsfs-142 and SVM combinations for primary classification.

b). The secondary stage classification performance with various features explained, using SVM and MLP classifiers is given in Table 2

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Table 1. Primary stage classification accuracy with various features using SVM and MLP classifiers along with classification time.

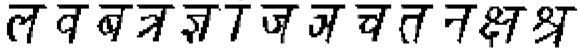
Feature Type	**Classifier**	**Avg. Classification accuracy (%)**	**Average Primary Classification time/ char (Milliseconds)**
NPW-64+ PSFS-78 (NpwPsfs-142)	MLP	98.2	3.8
	SVM	98.5	0.63
Grd-64+ PSFS-78 (GrdPsfs-142)	MLP	**99.4**	**3.7**
	SVM	98.9	0.63
TDIST-64+ PSFS-78 (TdistPsfs-142)	MLP	98.7	3.5
	SVM	98.4	0.65

The combination of gradient(Grd-64) and secondary stage feature set (SSFS-75) is performing as compared to other combinations in presence of SVM classifier. The performance of MLP classifier is 0.8 % less as compared to SVM.

c). Now, for final classification, there are subsets. The alphabet characters of these subsets are as follows:

1). Characters classified as characters having no side bar in primary stage classification. Characters are  This subset is called as N_Bar.

2). Characters classified as characters having side bar in primary stage classification and the characters classified as characters with two / more touches with the head line in secondary stage classification. Characters are:  This subset is called as TT_Bar.

3). Characters classified as characters having side bar in primary classification and the characters classified as characters with single touch withthe head line in secondary stage classification. Characters are:  This subset is called as ST_Bar.

In order to perform final recognition, the characters of each category are recognized using combination of three features i.e. Grd-64, NPW-64 and TDIST-64 each having 64 features giving 192 features in total. The average recognition accuracy on each set with average final stage classification time / character in milli-seconds is given in Table2. The average classification accuracy mentioned here does not include the classification error mentioned in primary and secondary stages. This is due to the final individual stage only.

Table2. Secondary stage classification accuracy based on training based model with various features using MLP and SVM classifiers.

Feature Type	**Classifier**	**Average Classification Accuracy**	**Average Secondary Classification time/ char (Milliseconds)**
Grd-64+ SSFS-75 (GrdSsfs-139)	SVM	98.3	0.6
	MLP	**99.1**	**2.6**
Tdist-64+ SSFS-75 (TdistSsfs-139)	SVM	98.1	0.6
	MLP	98.5	2.3
NPW-64+ SSFS-75 (NpwSsfs-139)	SVM	97.6	0.7
	MLP	98.1	2.5

Table 3. Final stage recognition performance of some features with MLP and SVM classifiers for all three Devanagari alphabet subsets.

Devanagari Alphabet Subset	**Features set**	**Classifier Type**	**Avg.Clas. Accuracy (%)**	**Avg. Final Stage Class. time/ char (ms)**
N_Bar	Grd-64+TDIST-64+NPW-64 (GrdTdistNpw-192)	SVM	95.6	1.8
		MLP	97.6	5.6

TT_Bar	Grd-64+TDIST-64+NPW-64 (GrdTdistNpw-192)	SVM	90.3	1.9
		MLP	91.1	5.8
ST_Bar	Grd-64+TDIST-64+NPW-64 (GrdTdistNpw-192)	SVM	93.8	1.8
		MLP	95.8	5.7

The recognition performance of this combination is different on different Devanagari alphabet subsets. The recognition rate on N_Bar and ST_Bar subsets is higher as compared to TT_Bar subset. The reason is that the TT_Bar subset contains large number of conflicting pairs of characters. It is difficult to distinguish such characters, even some times visually. 2.

The features used in primary, secondary and final stage recognition of Devanagari handwritten characters is known as DFS (Devanagari Feature Set). It comprises 345 features, where 142 features are used in the primary stage, 139 features are used in the secondary and 192 features are used in the final stage recognition. Here 64 features due to gradient are common in all the three stages. It is clear from our previous discussion that the characters of subset N_Bar have to pass through two classifiers and the characters of subsets TT_Bar and ST_Bar have to pass through three classifiers for final recognition. We rather suggest to use SVM classifier for primary and secondary stage classification as it gives minimum classification error on each stage. The recognition rate in percentage and average recognition time /character in milliseconds using SVM classifier for both primary and secondary stages and SVM or MLP classifier in final stage are given in Table 11. The results have been recorded by testing complete Devanagari character recognition system on all four test subsets using cross validation.

Time period underlined means time period used for primary or secondary stage classification using MLP classifier. In this three stage recognition scheme, even if we use SVM classifier for final stage recognition instead of MLP, the recognition rate is 93.0% which is 1.2% less as compared to using MLP as a classifier for final stage recognition. The time period with a MLP as final stage classifier is about 1.55 times large as compared to the time period with SVM classifier. Our first choice is to use MLP classifier and the second choice is to use SVM classifier for final stage recognition. For primary and secondary stage classification, we have already suggested to use SVM classifier.

Table 4. Recognition rate in percentage and average recognition time /character in milliseconds using SVM classifier for primary, secondary stages and SVM or MLP classifier in final stage.

Clas. for F. Stage	Alphabet Characters Subset			
	N_Bar	TT_Bar	ST_Bar	Avg.
MLP	9.3 ms (3.7+5.6)	12.1 ms (3.7+2.6 +5.8)	12.0 ms (3.7+2.6 +5.7)	11.1 ms
	96.8%	91.4%	94.5%	94.2%
SVM	5.5 ms (3.7+1.8)	8.2 ms (3.7+2.6 +1.9)	8.1 ms (3.7+2.6 +1.8)	7.2 ms
	95.2%	89.1%	94.8%	93.0%

V. DISCUSSIONS AND CONCLUSION

The classification time of MLP classifier is very high as compared to SVM but the recognition error is low for our application consisting of 43 classes. It is essential to divide the Devanagari dataset into subsets so that the classification time may be reduced without compromising accuracy.

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