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Research paper

Online Handwritten Gurmukhi Character Recognition using Hybrid Feature Set

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Abstract

Online handwriting character recognition is gaining attention from the researchers across the world because with the advent of touch based devices, a more natural way of communication is being explored. Stroke based online recognition system is proposed in this paper for a very complex Gurmukhi script. In this effort, recognition for 35 basic characters of Gurmukhi script has been implemented on the dataset of 2019 Gurmukhi samples. For this purpose, 32 stroke classes have been considered. Three types of features have been extracted. Hybrid of these features has been proposed in this paper to train the classification models. For stroke classification, three different classifiers namely, KNN, MLP and SVM are used and compared to evaluate the effectiveness of these models. A very promising "stroke recognition rate" of 94% by KNN, 95.04% by MLP and 95.04% by SVM has been obtained.

Keywords: *Feature extraction; Gurmukhi script; K-nearest neighbor; online recognition; Support Vector Machines.*

1. Introduction

In this digital age, easiest and a more personalized manner of communication between computers and users is natural handwriting. Online handwriting recognition system is emerging area of research today. Since everyone uses touch screen devices such as mobile phones, laptops, tablets and many more
gadgets to fulfill their needs but users are still unable to use their native language as a system of communication with the electronic items of daily use. In Indian context, it is difficult to communicate with computers for scripts like 'Gurmukhi' and 'Devanagiri' due to large set of alphabets and complex nature of typing of these scripts. Therefore, it is required to develop a user interface in which users can communicate in their own handwriting with computers. Online handwriting recognition system can replace the need of entering data through keyboards which is time consuming process and is also not suitable to people who are illiterate [1,2]. There are also various problems associated with handwriting recognition system. To achieve high degree of accuracy for handwriting recognition system is tedious task because of the variations in the writing styles. Variations in writing styles exist among different writers because every individual possesses their own style of writing in terms of speed, position or size of writing characters. Variation also exists within same writer due to different situations in which writer writes, it also depends upon the mood of the writer [3,4]. Online handwriting recognition system can also be called as real time processing because as we write characters they are recognized by the system. In this system, input is provided using pen based devices such as digitizer tablets, pads etc. Such device captures the sequence of (x,y) coordinates in the space as the character is written which can be called as a stroke. Stroke can be defined as trace of the tip of pen between pen-down and pen-up events [5]. Research in handwriting recognition has been ongoing for decades and a lot of research has been done on languages like English, Chinese, Japanese and Korean, however, a limited work for Gurmukhi script has been carried out [1]. Therefore, this work is aimed at developing efficient system to recognize strokes for online recognition of handwritten Gurmukhi script. This paper is divided into nine sections. This section outlines the basic concepts on online recognition system. Section 2 provides description about Gurmukhi script. Section 3 describes the previous work done in the field of online handwritten character recognition system. Section 4 describes the complete methodology involved in the process of online recognition. Section 5 describes how the handwritten data is captured for recognition and also outlines the preprocessing methods applied on the acquired data. Section 6 explains about the features extracted and their organization for recognition. Section 7 explains the three classifiers used for stroke recognition which are KNN, MLP and SVM. Section 8 presents the final results obtained for online recognition of handwritten Gurmukhi script. Finally, Section 9 concludes the work done on online recognition system.

2. Gurmukhi Script

The dictionary meaning of word 'Gurmukhi' is "Exactly as the Guru said". The Guru Granth Sahib Ji is written in Gurmukhi script and this script was standardized by Guru Angad Dev Ji, the second guru of Sikhism during 16th century. Gurmukhi is script used by Sikhs and Hindus primarily for writing Punjabi language [6].Gurmukhi script is cursive, written from left-to-right direction and in top-down approach. Gurmukhi script doesn't have concept of upper and lower case letters.

Punjabi language consists of 41 consonants, 9 vowels (laga matras), addak to duplicate sound of consonant, bindi and tippi for nasal sounds, 3 subjoined forms of the consonant ‘Rara’, ‘Haha’ and ‘Vava’ [1]. A word in Gurmukhi script can be broken into 3 horizontal zones; upper zone, middle zone and lower zone. The ‘upper zone’ is region above the headline where some vowels and sub-parts of vowels exist in. The ‘middle zone’ is area below the headline, where consonants and some sub-parts of vowels reside and lastly the ‘lower zone’ area below middle zone where some ‘*matras*’, vowels, half-characters reside. Upper and middle zone have a separation by headline which is also known as siro rekha [7]. Table 1 represents character set of Gurmukhi script.

Table 1: Character set of Gurmukhi script.

Basic Characters(Consonants)					Special Consonants
ੳ	ਅ	ੲ	ਸ	ਹ	ਸ਼
ਕ	ਖ	ਗ	ਘ	ਙ	ਖ਼
ਚ	ਛ	ਜ	ਝ	ਞ	ਗ਼
ਟ	ਠ	ਡ	ਢ	ਣ	ਜ਼
ਤ	ਥ	ਦ	ਧ	ਨ	ਫ਼
ਪ	ਫ	ਬ	ਭ	ਮ	ਲ਼
ਯ	ਰ	ਲ	ਵ	ੜ	

3. Related Work

This section provides brief literature review on the researches done in the field of online and offline handwritten character recognition. From literature survey it has been inferred that various techniques are followed by authors for recognition of various languages. Gurpreet Singh and Manoj Sachan [8] in their work on online recognition system explained in detail of the processes involved in the online recognition system. They have also discussed about the various features and classification schemes like rule based, structural or statistical models. In case of rule based and structural methods, rules for recognition are robust and reliable whereas for statistical models, fixed number of features define the shape of the stroke [1]. Various features have been extracted for recognition in the past, namely structural or shape based features, x-y traces, direction code based features, projection histograms, zonal density, distance profiles, background directional distribution (BDD) features, curvature features, region based features etc. Also, various recognition algorithms have also been experimented which includes elastic matching, rule based methods, distance time warping (DTW), artificial neural network (ANN), Hidden Markov Model (HMM), K-Nearest Neighbor (KNN) and Support Vector Machines (SVM).

4. Methodology

Data acquisition, preprocessing, feature extraction and classification are important phases of online handwriting recognition process. This section provides brief description on these phases.

Stroke capturing: Each character has been mapped on x-y plane and traces of each stroke have been captured using pen based devices like PDAs, digitizers etc. The complete database is explained in Section 4.

Preprocessing: After the x-y traces have been captured, they are preprocessed so that further features can be extracted. Preprocessing phase in online recognition system is performed to remove noise, distortions or unwanted information in the database due to hardware or software limitations. Five preprocessing steps are performed namely, size normalization and centering of strokes, interpolation of missing points, removal of duplicate points, smoothing of stroke, re-sampling of stroke.

Feature extraction: Feature extraction phase in online handwriting recognition is very important as recognition accuracy largely depends on this step. The features extracted for this work are elaborated in Section 5.

Classification: KNN, MLP and SVM are classification models used for recognition of strokes and have been implemented using cross validation and percentage-split technique.

The complete methodology for online handwritten recognition of Gurmukhi script has been shown in form of flowchart in Figure 1.

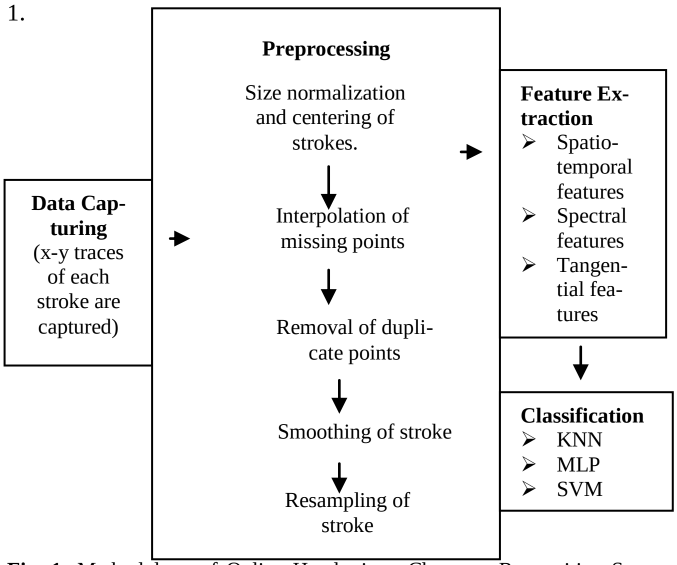


Fig. 1: Methodology of Online Handwritten Character Recognition System.

5. Data Collection and Preprocessing

Handwritten data is captured using pen based devices through which writer is able to write the handwriting samples on the writing pad. Handwritten data used for online recognition process in the form of (x,y) coordinate points captured in a time sequential manner by pen or stylus tip movement. The set of these coordinate points make a stroke. Pen trace is sampled at constant rate due to which coordinate points are uniformly distributed in time and not in space.

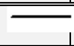
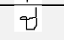
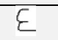
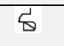
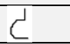
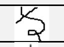
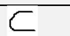
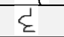
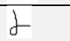
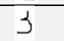
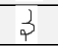
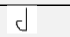
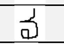
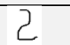
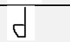
5.1 Data collection

As the characters in Gurmukhi script are formed with the combinations of different strokes. Therefore, stroke recognition forms the important part in the process. It is required that stroke classifier is trained to recognize the strokes. For each stroke, x-y traces obtained using digital pen on the writing pad between successive pen-down and pen-up events have been recorded. Total of 2019 samples have been considered written by different writers. Irrespective of the zone in which the stroke falls, 32 stroke classes have been formed using these samples to build the model for recognition. Table 2 contains the strokes, stroke IDs and the number of samples associated with each stroke.

5.2 Preprocessing

Preprocessing in online recognition system is required to remove the distortions that persist due to hardware or software deficiencies. Noise can be in form of irregular size of the stroke, jitter in the text, missing points in the coordinates while capturing the pen movements which depends upon the speed of handwriting, right or left bends, accidental pen lifts, pen stationary or moving slowly give rise to redundancy, unequal distances between adjacent points [2]. To remove such kind of imperfections from the database five preprocessing steps are performed which is removal of duplicate points, size normalization, centering, interpolation of the missing points, re-sampling of the points.

Table 2. Gurmukhi strokes used for recognition.

S t r	S t	S a	S t	S t	S a	S t	S t	S a
	121	62		167	65		196	70
	141	62		168	61		200	70
	145	68		170	60		202	60
	162	65		172	64		204	67
	146	64		174	62		207	60
	147	51		176	70		198	60
	149	62		179	61		211	64
	151	65		191	60		212	62
	155	59		183	65	-	-	-
	157	70		186	60	-	-	-
	161	60		187	70	-	-	-
	164	60		193	60	-	-	-

After the stroke has been captured, it is preprocessed to extract the features from the x-y traces. With the help of size normalization and centering, every stroke normalizes to same size and also centering to constant frame with text placed at fixed distance from origin. Stroke captured with high speed will have missing points. Hardware limitations can also result to missing points. Therefore, interpolation of missing points is necessary to achieve accuracy during recognition. Duplicate points are aggregation of excessive points in some part of the stroke while writing. So, it is required to remove these excessive points from the stroke to achieve equally spaced re-sampling points. Flickers are introduced into the handwriting due to individual writing style and also due to hardware. Therefore, smoothing is required for recognition. Re-sampling is performed to fix the number of points in the stroke and at the same time preserve the original shape of the stroke. It has been observed from the literature survey that best results are obtained when the number of re-sampled points is 64. After implementation of preprocessing steps, 64 preprocessed x-y traces of the each stroke are obtained in 300x300 window size [2].

6. Feature extraction

Feature extraction phase in online handwriting recognition is very important as recognition accuracy largely depends on this step. After preprocessing phase, features are extracted to obtain three different representations of the stroke for stroke classification. Three different features have been extracted in MATLAB, namely spatiotemporal features, spectral features and tangential features. These features are explained below:

6.1 Spatiotemporal Features (Pxy)

These are the 64 preprocessed x-y traces of each stroke and this feature set is referred as Pxy. A stroke obtained in data acquisition stage is a sequence of data points, where consecutive data points have uniform temporal separation. The preprocessed stroke is made up of sequence of predetermined data points that have homogeneous spatial separation along its path. Representation of these strokes has been shown in equation (1):

$$HS = [hs1 hs2 \ldots\ldots\ldots\ldots hsn]T \tag{1}$$

Where HS represents the stroke, hsi = (xsi, ysi) signifies coordinates of ith data point and 'n' represents number of data points in a stroke. For the present work, 'n' is 64. Spatiotemporal features acquire the information about the chronological sequence of the data points from positional coordinates. The temporal information of the stroke gets retained in the preprocessed stroke. These features are low level and point oriented features and can be called as local features.

6.2 Spectral Features (Sxy)

Spectral features can also be called as high level features and they belong to frequency domain. These features are referred as Sxy. Global features when used with local features represent the combination of high and low level features. Fast Fourier Transform (FFT) has been used to convert stroke from time domain to frequency domain. FFT representation of the stroke is provided in equation (2):

$$hw = [h_{w_{x+iy}}]T \tag{2}$$

Where $h_{w_{x+iy}} = FFT(\bar{x} + i\bar{y})$,
$\bar{x} + i\bar{y} = [xs1 + ys1 \quad xs2 + ys2 \ldots\ldots\ldots\ldots\ldots\ xsn + ysn\ ]T$.

Quick change in the x or y coordinate in the signal, produces high frequency content in the Spectra. Low frequency contents provide general shape properties and high frequency content captures the finer details of the object.
Fourier Descriptors (FDs) have the property of invariance to affine shift in the starting point and to affine shape transformations like translation, rotation, scaling and mirror reflections. Only a small number of Fourier descriptor coefficients are enough to represent the handwritten character and FDs allow complete reconstruction of the original shape of the character. 2019 FFT feature vectors are obtained corresponding to 2019 preprocessed strokes. Frequency information of the signal has been contained by each FFT feature vector, consisting of 64 complex coefficients. Feature vectors obtained through FFT, are further utilized for classification.

6.3 Tangential features (Txy)

Tangential features can be represented as follows:

$$\alpha_{p_{n-1},p_n} = \arctan\left(\frac{y_{n-1} - y_n}{x_{n-1} - x_n}\right) \tag{3}$$

and the feature vector for tangential features is represented as follows:

$$F = [\alpha_{p_1,p_2}, \alpha_{p_2,p_3}, \ldots\ldots\ldots\ldots\ldots\ldots\ldots \alpha_{p_{n-1},p_n}] \tag{4}$$

Direction of text matters in tangential features which mean if the text is written from left to right; it will yield totally different features than text which is written in right to left direction. For this work, from the preprocessed samples of every stroke, tangential features are extracted. From 2019 preprocessed strokes, equal numbers of tangential vectors are obtained. These features are referred as Txy. These features are used in different combinations with different classifiers and thus proposing hybrid method of using these features in different combinations. 3 briefs about the features extracted.

Table 3. Features extracted to build classification models.

Features Extracted	Name	Explanation
Spatiotemporal features	P_{xy}	Preprocessed x-y traces of each stroke (2019 spatiotemporal feature vectors are obtained).
Spectral features	S_{xy}	Preprocessed strokes in frequency domain (2019 spectral feature vectors are obtained).
Tangential features	T_{xy}	Tangents obtained at every pen tip position along the pen trajectory for all strokes (2019 tangential feature vectors are obtained).

7. Classification

In this section, three types of classifiers are briefly explained which has been experimented for stroke classification. From the n this work. Classification models are obtained using two methods: cross validation and percentage split. In k-fold cross validation method, the original sample set is randomly partitioned into equal sized k subsample sets. One of the subsample set is kept as validation data for testing the model and k-1 subsample set are used for training purpose. Cross validation technique is repeated k times in such a way that each of the k subsample sets are used exactly once. After that, k results obtained are then averaged to single estimation. On the other side, percentage split method splits the sample data into two parts. Out of the two parts, one part is kept as training data and the other as validation data. User decides the percentage at which data splits and in the same way k in the cross validation technique.

7.1 K-Nearest Neighbor (KNN)

KNN can be classified as lazy or instance based learning in which unknown pattern is related to some known pattern in accordance with some distance or other similarity function. For classification of the sample, it depends on the majority vote of its neighbor. In KNN, k depicts the number of neighbors to be considered and unknown sample is assigned the class of majority of the neighbors. Similarity function which can be used to find the nearest neighbors is Euclidean distance between the testing and reference points in order to find the nearest k neighbors.

7.2 Multilayer Perceptron (Mlp)

MLP is very popular feed forward artificial neural network architectures used in online handwriting recognition system. It uses supervised learning technique called back-propagation through which network is trained. MLP is composed of three layers: Input layer, hidden layer and output layer and each layer is fully connected to the next layer. It can classify data which are not linearly separable [19].

7.3 Support Vector Machines (MLP)

SVM is supervised learning method that can be applied to classification or regression. SVM requires fixed length of feature vector of the stroke, irrespective of instance or class it belongs. Length of feature vector is fixed in this work which is 64. It is a binary classifier which takes the input data and classifies it to one of the two distinguished classes by constructing the maximum margin hyper plane. In case classes are not linearly separable, SVM uses kernel functions in order to map data to higher dimensional space to increase the separability. One such kernel function is polynomial kernel. For this work, polynomial kernel function is used. If the problem consists of more than two classes, then algorithm breaks the multiclass into multiple binary classification problems and multiple binary SVM is designed [18].

8. Results and Discussions

Three different types of features extracted, namely P_{xy}, S_{xy} and T_{xy} are used to build classification model for recognition of the stroke. KNN, MLP and SVM are the classifiers used.

Table 4: Parameters of KNN, MLP and SVM.

Classifier	Features	Parameters	Options/ Values
K-Nearest Neighbor (KNN)	P_{xy}, S_{xy}, hybrid of P_{xy} and S_{xy}, hybrid of P_{xy} and T_{xy}	K	1,3,5,7
Multilayer Perceptron (MLP)	P_{xy}, S_{xy}	Size of Hidden layer (a)	48
	hybrid of P_{xy} and S_{xy}, hybrid of P_{xy} and T_{xy}	Size of Hidden layer (a)	80
	P_{xy}, S_{xy}, hybrid of P_{xy} and S_{xy}, hybrid of P_{xy} and T_{xy}	Learning rate (0-1)	0.3
		Momentum (0-1)	0.2
		Neurons in output layer	32
		Training time	500
Support Vector Machines (SVM)	P_{xy}, S_{xy}, hybrid of P_{xy} and S_{xy}, hybrid of P_{xy} and T_{xy}	Penalty parameter (C)	50,100,150
		Kernel	Poly-kernel
		Tolerance parameter (ε)	0.001

literature survey, it has been inferred that these classifiers have shown good accuracy rates for the online handwritten character recognition process. Therefore, these classifiers are used for obtaining accuracy

2019 samples have been used to train the recognition system. Parameters for these classification models have been empirically optimized to get best accuracy. For the KNN system, accuracies are obtained at k = 1,3,5,7. For MLP, the number of neurons in the output layer is 32 which are equal to the number of stroke classes. Learning rate of back-propagation algorithm is set at 0.3 which is its default value. Learning rate can be between 0 and 1. Momentum rate of back-propagation algorithm can take values between 0 and 1. Its value is set at 0.2 which is the default value. In this work, four types of feature sets are used to train the MLP. For the feature sets Pxy and Sxy, size of the hidden layer is 48 in the architecture. Size of hidden layer is decided using formula: (attributes +classes)/2. For hybrid of Pxy and Sxy, size of hidden layer is 80 and for hybrid of Pxy and Txy, size is 80. In case of SVM, it is used with poly kernel function. Parameters of SVM, penalty parameter (c) and learning rate (γ) have been optimized. Tolerance parameter is set at default value of 0.001. Also, these classification models are implemented using cross validation and percentage split technique. Accuracies are obtained for two different values of k in cross validation and at 66% split of data into testing and training set. Parameters of KNN, MLP and SVM are given in Table 4. Table 5 represents the accuracy obtained by using different combinations of features with KNN classifier using cross validation and percentage split method.

Table 5. Feature wise accuracy with KNN classifier**.**

Feature	Accuracy(%) with K-Nearest Neighbor (KNN)		
	Cross Validation		Percentage Split (66%)
	Fivefold	Tenfold	
P_{xy}	88.75	89.20	88.33
S_{xy}	80.28	80.68	78.13
Hybrid of P_{xy} and T_{xy}	82.76	83.65	82.21
Hybrid of P_{xy} and S_{xy}	93.90	94.00	92.85

Table 6 represents the accuracies obtained by using different combinations of features with MLP classifier using cross validation and percentage split method.

Table 6. Feature wise accuracy with MLP classifier.

Feature	Accuracy(%) with Multilayer Perceptron (MLP)		
	Cross Validation		Percentage Split (66%)
	Fivefold	Tenfold	
P_{xy}	89.15	89.89	89.21
S_{xy}	86.08	86.87	85.27
Hybrid of P_{xy} and T_{xy}	89.35	90.44	88.62
Hybrid of P_{xy} and S_{xy}	93.85	95.04	94.60

Table 7 represents the accuracies obtained by using different combinations of features with SVM classifier using cross validation and percentage split method.

Table 7. Feature wise accuracy with SVM classifier.

Feature	Accuracy(%) with Support Vector Machines (SVM)		
	Cross Validation		Percentage Split (66%)
	Fivefold	Tenfold	
P_{xy}	89.45	89.64	89.50
S_{xy}	84.39	84.94	83.96
Hybrid of P_{xy} and T_{xy}	88.45	88.45	88.33
Hybrid of P_{xy} and S_{xy}	94.99	94.99	95.04

It can be inferred from the results shown above that highest accuracy of 95.04% has been achieved by MLP and SVM. Hybrid feature set of Pxy and Sxy has provided the highest accuracies for all the classifiers. It has also been observed experimentally that other feature sets have also shown good accuracies above 80.28% except for the one case of KNN for feature Sxy i.e. 78.13%. Highest accuracy achieved by KNN classifier is 94% for hybrid feature set of Pxy and Sxy which shows that KNN also gave good performance. Cross validation has provided better results than percentage split method.

9. Conclusion

In this paper, stroke based online handwriting recognition system has been developed for Gurmukhi script. Input data is collected in the form of handwritten strokes. For the work, 32 stroke classes have been considered and samples which are belonging to each class are given in Table 3. Stroke recognition is done on 2019 samples. Spatiotemporal, spectral and tangential features are extracted. Hybrid combination of these features has been used with different types of classifiers. Three types of classification algorithms have been used namely KNN, MLP and SVM. These algorithms are applied using two techniques: cross validation and percentage split technique.

From the results, it has been observed that cross validation technique provides better results than percentage split technique. Also, for tenfold cross validation results are better than fivefold cross validation. It is because cross validation technique has many advantages over percentage split method that it improves the generalization ability of the classifier having optimized parameters by averaging the classification accuracies of k classifiers. It makes full use of limited data by ensuring that all of the dataset is involved in training and validation for classification. It uses every data point exactly once as test set and trained k-1 times irrespective of how the data is divided. But the problem with the cross validation is that it takes k times computation to make an evaluation.

Highest accuracies are obtained using MLP classifier in most of the cases and also, other two classifiers SVM and KNN are producing good accuracies. It has been observed that SVM and KNN are better than MLP in terms of speed but MLP has high noise tolerance compared to them. It has also been observed from the experimental results that KNN classifier works best when the value of k is kept at 1 and also optimum value of k depends upon the data. It could be if test data have high similarity with the training data. Among the features extracted, highest accuracy has been achieved using hybrid of spatiotemporal and spectral features and other features are also providing good results. The highest accuracy of 95.04% has been obtained using MLP and SVM classifier.

A good accuracy has been achieved in this work to recognize the strokes of the Gurmukhi script. In future, the accuracy can be further improved by adding other features and using hybrid model of classifiers. In the contemporary research ongoing in other regional scripts (Bangla, Tamil, Malayalam etc.), researchers are trying hybrid methods using script specific features [20, 21]. In future, verified methods applicable to other scripts can also be explored to improve the accuracy of existing techniques.

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