Recognition of online handwritten Gurmukhi characters based on zone and stroke identification

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Abstract. Handwriting recognition is a technique that converts handwritten characters into a machine-processable format. Handwritten characters can either be presented to machine online or offline. A good amount of research in this area has been carried out for English, Chinese, Japanese and Korean languages. Research is also going on for Indian languages on developing online handwriting recognition systems. Headline and baseline are common features in most Indic languages which divide a character into three zones, namely, upper, middle and lower zones. Identification of headline and baseline is a major task for classification of strokes located in these three zones. A zone identification algorithm is proposed and tested in this text for online handwriting recognition of Gurmukhi script. The strokes are grouped into these separate zones and are recognized based on respective support vector machine model for each zone. A rule-based approach has also been applied and tested for generation of characters from the set of recognized strokes. In this work, an accuracy of 95.3% has been achieved for zone identification and an accuracy of 74.8% has been achieved for character identification for Gurmukhi script. This accuracy has been achieved when the recognition engines of three zones were tested on the dataset of 428 characters each written by 10 users.

Keywords. Gurmukhi script; SVM; handwriting recognition; pre-processing; post-processing.

1. Introduction

Computer human interface is one of the buzzwords these days owing to the invention of touch- and pen-based input devices in PDAs, and other computing devices. With the invention of these touch based interfaces, handwriting has become an important medium for interacting with the computers. In these devices, a sensor picks up the movements of pen or fingers between successive PEN UP/PEN DOWN events. This kind of data is known as digital ink and can be considered as a dynamic representation of handwriting, which can be directly converted to stream of characters of a language using online handwriting recognition system.

Online handwriting recognition system is the system by which a computer can recognize characters and other symbols written by hand in natural handwriting. A number of applications can be created to facilitate the processing of information that is mostly collected using forms to be filled by the people with these systems. A large amount of work in handwriting recognition has been done for simplified Chinese, traditional Chinese, English, Japanese, and Korean languages [1–4]. However, a little attention has been devoted to Indian scripts. Gurmukhi is the script used to

write Punjabi language in India. Graphemes (strokes) in Gurmukhi script can appear in three different zones, namely, upper, middle and lower zones as shown in figure 1. The current work presents an approach to identify the zone in which the grapheme appears and then recognizes it with respective recognition engine giving zone wise accuracy. In this work, 7 stroke classes in upper zone, 80 stroke classes in middle zone, and 12 stroke classes in lower zone have been considered. The work also explores the post-processing requirements of conversion of strokes into characters of Gurmukhi script.

This paper is organized into seven sections. This section introduces basic concepts behind the work. Section 2 describes the literature related to the problem. Section 3 describes Gurmukhi script and its features and how online handwritten data has been collected. This section also discusses various challenging issues in Gurmukhi script recognition and explains various stages of Gurmukhi character recognition system. Section 4 explains pre-processing steps applied on the collected data. This section also explains how various features have been calculated and then organized for recognition of strokes. Section 5 describes how classification models were chosen from the selected feature set. It also explains various parameters used for support vector machine to build the stroke classification model. Section 6 explains the zone identification

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Figure 1. Zone division of Gurmukhi characters.

algorithm that is used to identify the lower and upper baselines from a set of Gurmukhi strokes. This section also analyses the results of zone identification algorithm as well as the recognition of characters using rule based post-processing algorithm. Section 7 concludes the work done with salient findings.

2. Related work

This section briefly reviews the literature on online handwriting recognition systems. In the computing environment, keyboards had been an effective interface for interacting with computers, but with advancements in computational technology, and advent of touch-based systems, a more natural way of interacting with the computers is being explored. Tappert *et al* [1] reported a survey on online and offline handwriting recognition systems for Japanese, Korean, Chinese and English languages. Bellegarda *et al* [5] introduced the idea of recognizing handwriting using a computer-based method. The authors proposed a continuous parameter hidden Markov model-based approach to handwriting recognition systems. Dutta and Chaudhary [6] proposed a curvature feature-based recognition method for Bangla alphanumeric characters, and found the technique effective with two-stage feed-forward neural network. Garcia *et al* [7] presented a neural predictive system for online writer independent character recognition. A fixed number of predictive neural networks (NN) were used to model each letter by them. For 10 different writers, the system gave quite a good recognition rate and improvement in results was reported with the extension of the system to the durational HMM framework. Hu *et al* [8] proposed HMM-based algorithms for online handwritten character recognition. They achieved a writer independent recognition rate of 94.5% on 3,823 unconstrained online handwritten word samples from 18 writers covering a 32 word vocabulary. Takahashi *et al* [9] achieved a 90.0% recognition rate for 881 Kanji characters with fast HMM algorithm for handwriting recognition. Yaeger *et al* [10] presented number of innovations in application of artificial neural networks for classification of characters and word recognition. Plamondon and Sirhari [11] in their survey on online and offline handwriting recognition systems explained various processes involved starting from input to final

understanding/recognition of characters for a language. They have discussed categories of recognition methods, namely, structural/rule based methods and statistical methods in their work in order to recognize handwriting with pen-based devices. Structural/rule based methods define robust and reliable rules for recognition purposes. In statistical methods, shape of a graphical mark known as stroke or grapheme is described by fixed number of features, and the classes of these graphical marks are described by multidimensional probability distribution. Connell *et al* [12] proposed a recognition system for unconstrained online Devanagari characters. An accuracy of 86.5% with no rejects was achieved by them. Jain *et al* [13] in their survey on pattern recognition cited statistical, syntactical and structural, neural network and elastic matching techniques as common handwriting recognition methods experimented by researchers. Connell and Jain [14] presented a template matching algorithm for online character recognition. The authors used these templates as reference for efficient classification of characters using decision trees. Pechwitz and Märgner [15] proposed a baseline detection algorithm to detect the orientation of a word. They explained the importance of baseline as a precondition to a handwriting recognition system. Skew normalization and character segmentation can be performed with the help of baseline in any script. Garain *et al* [16] presented promising results for online recognition of handwritten characters in Devanagari and Bangla, the two major Indian scripts, by modelling the human motor functionality while writing characters. Vijayasenan *et al* [17] applied principal component analysis on online handwriting recognition in Tamil script. Joshi *et al* [18] presented an automatic recognition system for isolated handwritten Devanagari characters by linearizing consonant conjuncts. Bharat and Madhvanath [19] proposed a data driven HMM based online handwriting recognition system for Tamil script. The authors reported encouraging results for exploring the approach for other Indic scripts. Jayaraman *et al* [20] used a baseline detection approach in their pursuit to recognition of Telugu script. They explained a modular approach to recognize Telugu script distributing the strokes into three classifiers based on upper and lower baselines in Telugu script. Parui *et al* [21] presented two-stage HMM-based method for recognition of Bangla characters. Sharma *et al* [22] explored the implementation of elastic matching for online handwritten Gurmukhi strokes and further formed the character based on recognized strokes. A character set of 41 Gurmukhi characters was tested by them for 60 writers and a recognition rate of 90.1% has been reported. Swethalakshmi [23] proposed handwriting recognition system for Devanagari and Tamil scripts using SVMs. She analyzed performance of different SVM classifiers and compared it with HMM based classifier using spatiotemporal representation of strokes. The stroke recognition accuracies of 95.3%, and 92.1% have been reported in her work for Devanagari, and Tamil scripts, respectively. A character recognition accuracy of 89.9% for Devanagari script has also

been reported in this work. Sundaram and Ramakrishnan [24] proposed Tamil script specific post-processing schemes for improving the recognition rate of online handwritten characters in Tamil using nearest neighbor classifier. Sharma [25] proposed a post-processing algorithm for rearrangement of strokes to identify Gurmukhi characters from combination of strokes. The authors achieved a character level recognition accuracy of 81.0% for a set of 2,576 Gurmukhi words. Prasad *et al* [26] presented a divide and conquer technique based approach to recognize Kannada characters by dividing the strokes into various auxiliaries and using classifiers for each of the auxiliary to predict the Kannada character using a rule base. Sharma *et al* [27–29] worked on 49 classes for online handwritten character recognition of Gurmukhi script. They did not consider zoning in their work as the number of classes considered by them was limited. Hajj and Awad [30] presented an efficient handwriting recognition system for writer independent isolated letter recognition for English. They modelled pen trajectories for feature extraction and applied multi-stage support vector machines (SVMs) for classification of strokes based on zone. Sharma *et al* [31] presented a study of SVM based classifiers to develop online handwriting recognition system for Gurmukhi script. Kumar and Sharma [32] proposed a post-processing algorithm for generation of Gurmukhi characters from a set of intermediate strokes created by recognition system. In the current work, we have presented a Gurmukhi character recognition system. This system first identifies the zone of a stroke and then recognizes it. The recognized strokes are used to form the Gurmukhi character guided by a rule base. Motivated by speech recognition framework, Kopparapu and Lajish [33] proposed a novel framework for online handwritten Devanagari character recognition. A feature set called fuzzy directional

features (FDF) has been introduced by them. Three classifiers, namely, nearest neighbor classifier, dynamic time warping (DTW), and SVM, have been used by the authors to test the system. They reported a character level accuracy of 73.9% using FDF with SVM classifier. Table 1 illustrates some of the salient works done for developing online character recognition systems for Indic languages.

3. Gurmukhi script and data collection

In this work, we have addressed the problem of classifying different characters of Gurmukhi script in three zones and then classifying the strokes in each zone. Gurmukhi script is one of the popular scripts in north India. This is also popular in Punjab province of Pakistan. Besides, this script is very frequently used by Punjabis settled in Canada, USA, UK, Australia and other countries. Table 2 contains the characters used in Gurmukhi script. Writing style in this script is from left to right. Gurmukhi script contains 41 consonants as given in table 2(a). Out of these 41 consonants, there are 35 base consonants or akhars (A0–G4) and 6 consonants with subscript dot (A5–F5). ਊ, ਅ, ਏ are the three vowel holders in Gurmukhi script. A vowel holder is used when there is no consonant between vowel sounds. This script contains 10 vowel modifiers or mātrās, 9 of them as given in table 2 (b) have specified symbols (A7–I7). These are also known as dependent vowels and remaining one has no symbol and is known as *mukta*. A *mukta* is pronounced between each and every consonant wherever no other vowel is present unless otherwise indicated. Table 2(b) also exemplifies the usage of these dependent vowels with a consonant ਭ (A8–I8). The first column in table 2(b) (A6–I6) shows independent vowels

Table 1. Work done for Indic languages.

Language	References	Classifier	Dataset and recognition accuracy
Bangla	Dutta and Chaudhury [6]	Feed forward neural network	90.0% for Bangla numerals and 85.0% for Bangla characters
	Parui <i>et al</i> [21]	HMM	24,500 online handwritten isolated characters, 84.6% stroke level recognition accuracy
Hindi	Connell <i>et al</i> [12]	HMM and nearest neighbor stroke recognizer	20 writers wrote five samples of each character, 86.5% character level recognition accuracy with no rejects
	Joshi <i>et al</i> [18]	Subspace method for classification	94.5% accuracy for Devanagari characters
	Swethalakshmi [23]	Support vector machines	89.9% character recognition accuracy on a dataset of 3,774 words from 34 writers
	Bharath and Madhvanath [19]	Lexicon driven HMM and lexicon free HMM	87.1% recognition accuracy on 20,000 word lexicon when the two recognizers are combined
Kannada	Prasad <i>et al</i> [26]	Rule-based classifier	81.0% character recognition accuracy with 17,181 character samples
Punjabi	Sharma <i>et al</i> [22, 27–29]	Elastic matching, HMM	91.9% character recognition accuracy with 40 stroke classes
Tamil	Bharath and Madhvanath [19]	Lexicon driven HMM,	91.8% recognition accuracy with 20,000 word lexicon u
Telugu	Jayaraman <i>et al</i> [20]	SVM based classifier	83.0% character recognition accuracy

Table 2. Chart of Gurmukhi characters.

	0	1	2	3	4	5					
(a) consonants in Gurmukhi script											
A	ੳ	ਅ	ੲ	ਸ	ਹ	ਸ਼					
B	ਕ	ਖ	ਗ	ਘ	ਙ	ਖ਼					
C	ਚ	ਛ	ਜ	ਝ	ਞ	ਜ਼					
D	ਟ	ਠ	ਡ	ਢ	ਣ	ਨ਼					
E	ਤ	ਥ	ਦ	ਧ	ਨ	ਡ਼					
F	ਪ	ਫ	ਬ	ਭ	ਮ	ਲ਼					
G	ਯ	ਰ	ਲ	ਵ	ੜ						
		6	7		8						
(b) independent vowels, vowel modifiers and example usage of vowel modifiers with ਕ in Gurmukhi script											
A	ਆ		ਾ		ਕਾ						
B	ਇ		ਿ		ਕਿ						
C	ਈ		ੀ		ਕੀ						
D	ਉ		ੁ		ਕੁ						
E	ਊ		ੂ		ਕੂ						
F	ਏ		ੇ		ਕੇ						
G	ਐ		ੈ		ਕੇ						
H	ਓ		ੋ		ਕੇ						
I	ਔ		ੌ		ਕੇ						
		0	1	2	3	4					
(c) other symbols in Gurumukhi script											
I	ੰ	ੰਗ	ੰ	ੰ	ੰ	ੰ					
		0	1	2	3	4	5	6	7	8	9
(d) numerals in Gurumukhi script											
K	੦	੧	੨	੩	੪	੫	੬	੭	੮	੯	੯

used in Gurmukhi script. The vowel symbols can appear above, below, or to either side of consonants, or their respective vowel holders. There are some other symbols used in Gurmukhi script to represent nasal, duplicity and other sounds, as shown in table 2(c). The script has two symbols for nasal sounds *bindī* (10) and *ṭippī* (12), and one symbol which duplicates the sound of any consonant, namely, *addak* (13). The two remaining symbols *halant* (14) and *visarg* (11) are rarely used in modern Gurmukhi texts, and have been used occasionally in Sanskritised text or in dictionaries for extra phonetic information. Table 2(d) represents numeral digits written in Gurmukhi script. Seven Gurmukhi characters (ੳ, ੲ, ਚ, ਟ, ਤ, ਯ, ਵ) may also appear in the lower zone and are known as half characters (*paireen-characters*). These half characters have not been allocated any Unicode, and are dealt with functions using *halant*.

3.1 Some issues in Gurmukhi script recognition

In section 2, we surveyed online handwritten word/character recognition systems for some languages. The major issues tackled by authors in developing these systems include shape complexity of characters, presence and absence of baseline, features for recognition of characters,

and stroke/character level recognition. Following subsection explains some of the issues that play an important role in developing an online handwritten recognition system for Gurmukhi script.

3.1a Three zones of writing strokes: Gurmukhi characters are written in various styles that increase the difficulty in recognition of a particular character. Gurmukhi script characters may lie in three horizontal zones, namely, upper zone, middle zone and lower zone as depicted in figure 1. The upper zone denotes the region above the headline, where some of the vowels (ੈ, ੋ, ੌ) and sub-parts of some other vowels (ਿ, ੀ) reside, while the middle zone represents the area below the headline where the consonants and sub-parts of some vowels (ਿ, ੀ) are present. Middle zone consists of most of the Gurmukhi characters. The lower zone represents the area below middle zone where some vowels and certain half characters lie in the foot of consonants. A Gurmukhi character can be written with single or a combination of strokes, with stroke considered as smallest unit. These strokes may appear in a single zone, or combination of three zones described above. To initiate the recognition process, various classes of strokes have been identified. These stroke classes are

further divided into three zones, namely, upper, middle and lower zones to avoid confusion between similar looking strokes in three zones.

3.1b Variations in writing style: The personal characteristics in handwriting variations include writer's choice of strokes for writing same character. Different users write characters with different choices of strokes and their sequence. For example, in order to write the character ਝ, several combinations of strokes can be used as illustrated in figure 2, where each stroke is written without knowing the zone boundaries. Since all the strokes have been grouped according to the zone in which they appear, it is difficult to figure out zone boundaries by looking at the stroke. The sequence of strokes may also vary for writing a character leading to confusion at post-processing level as illustrated in figure 3 for character ਝ. While writing in Gurmukhi, the writer adds an upper bar on characters to end the word. A writer has also to add a middle bar in some characters that is similar in shape to the upper bar. Presence or absence of upper and middle bar with other strokes generates a different character in Gurmukhi. Some example combinations are shown in figure 4.

3.1c Presence of half characters: In addition to the problems mentioned above, another challenge is to handle strokes in lower zone that are half characters like *paireen* ਚ in ਕਿੱਯਾ and *paireen* ਚ in ਖੁਲ੍ਹੇ. In such cases, it becomes sometimes difficult to draw zone boundaries between the middle and lower zones, leading to difficulties in recognition of these half characters. These half characters may then conflict with other characters like ਝ, ਝ, ਝ, ਝ.

3.2 Steps involved in recognition of characters

In order to recognize online handwritten characters, the set of strokes goes through the phases as illustrated in figure 5. This section includes a brief description of these phases:

- An online handwritten stroke is written by a user on tablet using a touch device or pen device. Each stroke consists of x - y trace points between successive PEN DOWN and PEN UP movements.
- These strokes are then fed to stroke zoning phase which identifies the zone of the strokes, based on the relative position of strokes with respect to other strokes. The three zones in which a stroke may lie can be upper, middle or lower zone as illustrated in previous

Combination	Stroke(s) (zone)			Outcome
	1	2	3	
1	ㄥ (Middle)			ਝ
2	ㄥ (Middle)	— (Upper)		ਝ
3	γ (Middle)	ㄥ (Middle)		ਝ
4	γ (Middle)	ㄥ (Middle)	— (Upper)	ਝ

Figure 2. Example combinations of strokes for writing ਝ.

Combination	Stroke sequence (zone)			Outcome
	1	2	3	
1	ε (Middle)	ㄿ (Middle)		ਝ
2	। (Middle)	ε (Middle)		ਾ,ੲ (confused with ਝ)
3	ੴ (Middle)	— (Upper)		ਝ
4	ε (Middle)	। (Middle)	— (Upper)	ਝ

Figure 3. Example of sequence of strokes for writing ਝ.

Combination	Stroke number (zone)			Required outcome
	1	2	3	
1	੨ (Middle)			੨
2	੨ (Middle)			ਖ
3	੨ (Middle)	— (Middle)		ਖ
4	੨ (Middle)	— (Upper)		ਥ
5	੨ (Middle)	੨ (Middle)		੨
6	੨ (Middle)	— (Middle)	— (Upper)	ਥ
7	੨ (Middle)	੨ (Middle)	— (Middle)	ਥ
8	੨ (Middle)	੨ (Middle)	— (Upper)	ਧ
9	੨ (Middle)	੨ (Middle)	— (Middle)	ਖ

Figure 4. Examples of common ligatures for ਥ, ਖ, ਪ, ਧ.

Figure 5. Steps in character recognition.

subsection. The actual x – y points of the stroke are used in further processing.

- (c) After identifying the zone, the stroke points are pre-processed for extraction of feature in this step. During pre-processing, a noise or distortion that arises due to software limitations is removed from original stroke. Now, normalization and centering of stroke is done, where the input stroke is fitted into a fixed size window, and is moved to the central location. During writing of a stroke, some points might be missed by the touch sensor. These missing points are interpolated using Bézier interpolation technique. Jitters are removed from the stroke by averaging each point with its neighbors.

- (d) Features required for classification of strokes, as per model chosen, are now extracted from the strokes which have further been used for recognition of the strokes.
- (e) Support vector machine is next used for classification of strokes. The recognition accuracy using linear, polynomial, radial basis and sigmoid kernels are then calculated for different combinations of parameters.
- (f) After classification of strokes, post-processing steps are applied on the recognized strokes to identify the character formed using these strokes.

3.3 Data collection

Samples of Gurmukhi words have been collected using Dell Latitude XT3 Tablet PC. Individual strokes with their sequence have been recorded in XML format. An 800×800 interface for writing strokes is used. Each stroke consists of x – y traces of digital PEN on the touch screen between successive PEN DOWN and PEN UP movements. In the data collection phase, 44,301 samples of 2,000 unique Gurmukhi words containing 241,239 strokes have been collected from 124 different writers. The writers are chosen from various parts of Punjab, who are familiar with writing Gurmukhi script and are using Gurmukhi script in their day-to-day life. Among the users, there are school children studying in class 6 and above up to the degree/diploma level, Government officials at local offices in

Table 3. Upper zone strokes and their associated strokeIDs.

stroke	˘	˙	˚	˛	˜	˝	˞
strokeID	122	123	124	125	126	127	128
stroke	/	9	˘	˙	˚		
strokeID	130	131	132	133	134		

Punjab, research staff involved in development of Gurmukhi script and some commoners who have studied Punjabi at their school level. Based on the writing styles of users and stroke formation, the strokes' data is classified into two different classes, namely, *Class A* and *Class B*. *Class A* data consists of those strokes that have been written by users as per standard way of writing script in an unconstrained environment. While *Class B* data consists of those strokes that do not meet standards of script writing and are also written in an unconstrained environment. This is worth mentioning here that one needs to prepare a different set of rules for *Class A* and *Class B* data. Out of these strokes, 99 stroke classes that have a higher frequency of occurrence in *Class A* and *Class B* data have been identified and are further used in this work. The data collected from these users have been annotated at the stroke level with unique StrokeIDs associated with each stroke. Tables 3, 4 and 5 contain the strokes and the strokeIDs associated with them in three zones.

Table 4. Middle zone strokes and their associated strokeIDs.

stroke	—	ᳵ	ᳶ	᳷	᳸	᳹	ᳺ	᳻	᳼	᳽
strokeID	121	141	142	143	144	145	146	147	148	149
stroke	᳾	᳿	᳠	᳡	᳢	᳣	᳤	᳥	᳦	᳧
strokeID	150	151	152	153	154	155	156	157	158	159
stroke	᳨	ᳩ	ᳪ	ᳫ	ᳬ	᳭	ᳮ	ᳯ	ᳰ	ᳱ
strokeID	160	161	162	163	164	165	166	167	168	169
stroke	ᳲ	ᳳ	᳴	ᳵ	ᳶ	᳷	᳸	᳹	ᳺ	᳻
strokeID	170	171	172	173	174	175	176	177	179	180
stroke	᳼	᳽	᳾	᳿	᳠	᳡	᳢	᳣	᳤	᳥
strokeID	181	182	183	184	185	186	187	188	190	191
stroke	᳦	᳧	᳨	ᳩ	ᳪ	ᳫ	ᳬ	᳭	ᳮ	ᳯ
strokeID	192	193	194	195	196	197	198	200	201	202
stroke	ᳱ	ᳲ	ᳳ	᳴	ᳵ	ᳶ	᳷	᳸	᳹	ᳺ
strokeID	203	204	205	206	207	208	209	210	211	212
stroke	᳻	᳼	᳽	᳾	᳿	᳠	᳡	᳢	᳣	᳤
strokeID	214	215	216	217	218	222	223	224	225	226

Table 5. Lower zone strokes and their associated strokeIDs.

stroke	˘	˙	˚	˛	˜	˝	˞
strokeID	101	102	103	104	105	106	107

4. Pre-processing and feature extraction

For developing the recognition model for classification of strokes, 100 samples of each stroke from three zones have been selected from the database. The strokes are selected in equal proportion from all the users, so as to reflect all patterns for a single stroke. During pre-processing, a series of transformations is performed on the stroke points. These transformations are normalization, centering, interpolation and smoothing as explained in previous section. The standard algorithms as explained by Guerfali and Plamondon [34] and Trier *et al* [35] have been used to implement these transformations. After performing the pre-processing steps, we obtained a 500×500 window containing resampled 64 $x-y$ points. These resampled 64 points are *normalized features* that have been considered for building SVM based classification models.

5. Zone identification

Identification of the zone of a stroke is an important process in the recognition model proposed in this work. Identification of the zone is critical for further classifying the stroke. We have proposed an algorithm *MarkStrokeZone* in this work that identifies the zone of a given stroke. The original $x-y$ points of each stroke are utilized in this algorithm to identify the boundaries of middle zone: $MidY_{min}$ and $MidY_{max}$. We have considered top left corner of data capturing device as the origin in this work. As such, $MidY_{min}$ is upper and $MidY_{max}$ is lower boundary of middle zone. *Center* is average of $MidY_{min}$ and $MidY_{max}$ denoting the middle value of y -coordinate in middle zone. These boundaries once created are used to mark the zone of the stroke. As per statistics collected from database, first stroke mostly occurs in middle zone, so in the proposed algorithm it has been assumed that the first stroke is always written in middle zone. After identifying the middle zone boundaries of the stroke, zone identification is done for next sequence of strokes. Here, $StrokeY_{min}$ is the smallest y -coordinate and $StrokeY_{max}$ is the largest y -coordinate of new stroke. $Center_{new}$ is the average y -coordinate value of new stroke and denotes the center of new stroke. If $StrokeY_{max}$ of new stroke is less than $MidY_{min} + h$ (a pre-defined tolerance level calculated based on statistics of collected data), then stroke considered to lie in upper zone. Similarly, if new stroke's $StrokeY_{min}$ is greater than middle zone's $MidY_{min} - h$, then the stroke is considered to lie in lower zone. If the $StrokeY_{min}$ of the new stroke is greater than $Center$ and $StrokeY_{max}$ is less than $MidY_{max} + h$, then the stroke is considered in lower zone. For all other cases, the new stroke is considered to lie in middle zone. The strokes are sent to respective recognition engines for identification based on their zone. All the cases described above are illustrated in figure 6.

Figure 6. Cases of zone identification: (a) initialization of middle zone boundaries, (b) identification of lower zone stroke, (c) identification of upper zone stroke, (d) identification of middle zone stroke, (e) case for paireen alphabets, and (f) special case for handling upper bar.

5.1 Verification and validation of zone identification

The values of parameters used in zone identification algorithm *MarkStrokeZone* have been inferred by analyzing the data collected from all users involved in data collection phase. This algorithm has been verified on a dataset of 4,500 characters used in training phase. These characters consisted of 4,870 strokes in upper zone, 8,340 strokes in middle zone and 2,873 strokes in lower zone. In this verification phase, an accuracy of 95.6%, 99.5% and 96.2% has respectively been achieved for upper, middle and lower zones.

For validation of the proposed algorithm for zone identification, a set of 4,280 handwritten Gurmukhi characters has been collected from 10 new users, who have not

participated in the data collection activity for preparation of recognition models. This dataset consists of 15,297 strokes. Out of these 15,297 strokes; 4,632 strokes were in upper zone, 7,832 strokes were in middle zone and 2,733 strokes were in lower zone. Handwritten characters collected from these 10 users have been tested for zone identification and also for stroke recognition. Accuracy for zone identification is verified by manually visualizing the actual zone of stroke and the zone predicted by the zone identification algorithm. Table 6 depicts the accuracy of zone prediction for various strokes in upper, middle, and lower zones. Zone accuracy is defined as the number of strokes correctly marked in a zone upon total number of strokes marked for the zone. Average accuracy achieved for zone identification of strokes in upper, middle and lower zones attained in this work is 94.6%, 98.4%, and 92.8%, respectively.

Algorithm 1. Associating the zone to a stroke

Data: $MidY_{min}, MidY_{max}, Center$ /

* Globally Declared lower, upper boundaries of middle zone and center line

Input: $StrokeY_{min}, StrokeY_{max}, n$ /

* lower and upper boundaries of stroke and stroke sequence number

Result: Zone of the stroke $z = 1, 2, 3$ /* Upper Zone($z = 1$), Middle Zone($z = 2$), Lower Zone($z = 3$) */

Algorithm MarkStrokeZone($StrokeY_{min}, StrokeY_{max}, n$)

begin // Initialization* /

 set $z=0$;

if $n==0$ **then** /* first stroke */

begin

 set $MidY_{min} = StrokeY_{min}$;

 set $MidY_{max} = StrokeY_{max}$;

 set $Center = (StrokeY_{max} - StrokeY_{min})/2$;

end

else

begin

 set $h = (StrokeY_{max} - StrokeY_{min})/8$;

 set $Center_{new} = (StrokeY_{max} - StrokeY_{min})/2$;

if $(StrokeY_{min} \geq (MidY_{max} - h))$ **then**

begin

 set $z=3$;

end

else if $(StrokeY_{max} \leq MidY_{min} + h)$ **then**

begin

 set $z=1$;

end

else if $(StrokeY_{min} > (MidY_{min} - h))$ and $(StrokeY_{min} < (MidY_{max} + h))$

 and $(StrokeY_{max} > (MidY_{min} + h))$ and $(StrokeY_{max} < (MidY_{max} + h))$ **then**

begin

 set $z=2$;

end

else

begin

if $((StrokeY_{min} + Center_{new}) \geq (MidY_{min} + Center))$

 and $(StrokeY_{max} \geq (MidY_{max} - h))$ **then**

begin

 set $z=3$;

end

else if $((StrokeY_{min} + Center_{new}) \leq (MidY_{min} + Center))$

 and $(StrokeY_{min} \leq (MidY_{min} + h))$

 and $(StrokeY_{max} < (MidY_{max} - h))$ **then**

begin

 set $z=1$;

end

else

begin

 set $z=2$;

end

end

end

return z ;

end

6. Classification models

As mentioned earlier, SVM recognition models are used for classification of strokes after identification of zone for given stroke. As such, three classification engines/models for upper, middle and lower zones have been developed by selecting one hundred samples of each stroke. There are 1,200 samples in upper zone, 8,000 samples in middle zone, and 700 samples in lower zone that have been used to train the recognition engines. In this work, as mentioned in previous section, normalized x - y points have been used as feature. For the classification process, SVM with kernels, namely, linear,

polynomial, sigmoid, and RBF have been used in this work. Other parameters that have empirically been experimented in this work are learning rate (γ), penalty parameter (C) and tolerance limit of termination (ϵ). Recognition rates for different experiments have been obtained using k -fold cross validation for three values of k as mentioned in table 7. Table 7 also contains the values of other parameters considered in this work.

This is worth mentioning here that we have experimented 1,080 different SVMs based on these parameters in this work. Zone-wise k -fold cross validation optimal accuracy for the parameters considered in this work is given in table 8.

Table 6. Userwise zone identification accuracy.

User	Upper zone (%)	Middle zone (%)	Lower zone (%)	Overall zone identification (%)
User 1	91.4	98.6	94.8	94.9
User 2	96.7	99.6	97.7	98.0
User 3	94.4	99.0	94.3	95.9
User 4	95.3	99.8	94.7	96.6
User 5	98.1	97.8	81.5	92.5
User 6	92.3	96.6	98.0	95.6
User 7	95.3	97.3	85.8	92.8
User 8	94.9	99.5	93.5	96.0
User 9	91.7	97.5	92.5	93.9
User 10	95.9	98.6	94.7	96.4
Average	94.6	98.4	92.8	95.3

Table 7. SVM parameters.

Parameter	Options/values considered
Number of folds (k)	4, 5, 6
Kernel	Linear (0), Polynomial (1), RBF (2) and Sigmoid (3)
Learning rate [$\log_2(\gamma)$]	-15 (2) 3
Penalty parameter [$\log_2(C)$]	-5 (2) 15
Tolerance limit of termination (ϵ)	0.001

6.1 Stroke recognition

Stroke recognition accuracy is defined as the total number of strokes correctly classified over total number of strokes correctly marked for the zone. The stroke recognition accuracy for 10 users is illustrated in table 9. The average stroke recognition accuracies for upper, middle and lower zones are 96.3%, 94.6%, and 90.2%, respectively.

6.2 Character recognition

To predict a character from the set of strokes that appear after the recognition process, a rule-based approach has been developed. These rules define the combination of strokes to create a character. These rules have been developed by analyzing the collected dataset for various combinations of strokes in which character can be written. A post-processing

algorithm proposed by Kumar and Sharma [32] has been used to predict the character after the recognition of stroke. During the testing of recognition process, the test set consisted of 41 Gurmukhi characters, along with their combinations with two nasal symbols (◌ं, ◌ँ) *addak* (◌ੱ, ◌ੰ), and nine vowel modifiers (◌ੇ, ◌ਿ, ◌ੀ, ◌ੁ, ◌ੂ, ◌ੇ, ◌ੈ, ◌ੈ, ◌ੈ).

Character recognition accuracy of each user is shown in table 10, where it can be seen that for a character without mātrā and nasal symbols, the accuracy is in the range of 91.0–94.0% with an average of 92.9%. While recognizing complex character combinations with nasal, mātrās and both, the average accuracy goes down to 85.0%, 69.2% and 52.9%, respectively. The major reason behind decrease of recognition rates is the variations in sequence of strokes for writing these complex characters in Gurmukhi script. Overall character recognition accuracy achieved in this work is 74.8%.

7. Results and discussion

In this paper, a handwritten character recognition system for Gurmukhi script has been proposed. A zone identification algorithm for classification of strokes written in upper, middle and lower zones for Gurmukhi script has also been proposed, verified and tested. Recognition of a stroke has been done using SVM with a feature set of normalized x - y points of the stroke. Zone identification algorithm performs well with an overall accuracy of 95.3%. In an earlier experiment, [27] experimented with 40 classes on Gurmukhi handwritten character recognition system and

Table 8. Zone-wise optimum performance of SVM kernels.

Kernel	Lower zone performance (%) at ($k; \log_2(\gamma); \log_2(C)$)	Middle zone performance (%) at ($k; \log_2(\gamma); \log_2(C)$)	Upper zone performance (%) at ($k; \log_2(\gamma); \log_2(C)$)
Linear	94.7 (4; -7; -5)	92.3 (5; -7; -1)	88.1 (5; -7; -1)
Polynomial	94.7 (4; -1; 15)	93.0 (4; -7; -1)	91.8 (5; -13; 11)
RBF	89.3 (5; -15; 1)	86.5 (4; -15; 1)	86.3 (5; -15; 1)
Sigmoid	14.9 (3; -15; 5)	2.4 (4; -11; 15)	17.2 (4; -11; 3)

Table 9. Userwise stroke recognition accuracy.

User	Upper zone (%)	Middle zone (%)	Lower zone (%)	Overall stroke recognition accuracy (%)
User 1	95.7	91.5	85.1	90.8
User 2	97.0	97.2	94.1	96.1
User 3	97.2	97.4	90.8	95.1
User 4	95.3	93.0	90.8	93.0
User 5	97.4	93.6	93.6	94.9
User 6	95.3	95.2	86.0	92.2
User 7	96.9	93.8	92.1	94.2
User 8	96.6	95.8	89.5	93.9
User 9	95.4	95.2	88.5	93.0
User 10	96.1	93.7	91.9	93.9
Average	96.3	94.6	90.2	93.7

Table 10. Userwise character recognition accuracy.

User	Character without mātrās (%)	Character with mātrās (%)	Character with nasals and addak (%)	Character with nasals, addak and mātrās (%)	Average character recognition (%)
User 1	91.7	51.5	100.0	50.0	73.3
User 2	92.1	79.8	100.0	55.4	81.8
User 3	93.2	77.1	50.0	52.7	68.2
User 4	90.2	67.6	50.0	53.7	65.4
User 5	90.6	65.3	100.0	52.7	77.2
User 6	92.0	73.3	100.0	55.3	80.2
User 7	92.4	72.2	50.0	52.1	66.7
User 8	92.1	51.4	100.0	52.3	73.9
User 9	94.0	73.5	100.0	50.4	79.5
User 10	94.1	80.2	100.0	54.5	82.2
Average	92.2	69.2	85.0	52.9	74.8

achieved a character recognition accuracies of 87.4%, and 92.0% with elastic matching technique and HMM, respectively. In their study they collected 130 samples of each consonant. The overall stroke recognition accuracy achieved in this work is 93.7%, whereas the average accuracy achieved for identification of characters from recognized strokes is 74.8% considering all characters and its complex character combinations with nasals and mātrās. As a further work in this direction, one can experiment for achieving higher character recognition rates by building a statistical model for sequence of strokes, which would replace the rule-based approach used in recognition of characters in Gurmukhi script. To improve zone identification algorithm, one can work on dynamically calculating the zone boundaries based on the position of nearby strokes in the character.

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