# Study of Zone-Based Feature for Online Handwritten Signature Recognition and Verification in Devanagari Script

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**Abstract** This paper presents one zone-based feature extraction approach for online handwritten signature recognition and verification of one of the major Indic scripts–Devanagari. To the best of our knowledge no work is available for signature recognition and verification in Indic scripts. Here, the entire online image is divided into a number of local zones. In this approach, named Zone wise Slopes of Dominant Points (ZSDP), the dominant points are detected first from each stroke and next the slope angles between consecutive dominant points are calculated and features are extracted in these local zones. Next, these features are supplied to two different classifiers; Hidden Markov Model (HMM) and Support Vector Machine (SVM) for recognition and verification of signatures. An exhaustive experiment in a large dataset is performed using this zone-based feature on original and forged signatures in Devanagari script and encouraging results are found.

**Keywords** Online handwriting · Signature recognition · Signature verification · Zone-wise feature · Dominant points · SVM and HMM

## 1 Introduction

An online signature is a method of personal authentication biometrically to execute automated banking transactions, online voting system or physical entry to protected areas. Signatures are used for identifying different persons because each signature

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possess both static as well as some dynamic features [1]. Dynamic features include elevation and pressure signals which make each person's signature unique. Even if skilled forgers are able to produce the same shape of the original signature, it is unlikely that they will also be able to produce the dynamic properties of the original one. In this paper a zone based feature [2] extraction approach has been used for recognition and verification of online handwritten Devanagari signatures. Zone based features [2] have been used and shown efficient results in online character recognition purpose.

Several studies are available [1–12] for online handwritten signature recognition and verification in non-Indic scripts, but to the best of our knowledge no work is available for signature recognition and verification in Indic scripts. In our system, we perform preprocessing such as interpolating missing points, smoothing, size normalization and resampling on each stroke of the signature. Then each online stroke information of a signature is divided into a number of local zones by dividing each stroke into a number of equal cells. Next, using the present approach, named ZSDP, dominant points are detected for each stroke and next the slope angles between consecutive dominant points are calculated separately for the portion of the stroke lying in each of the zones. These features are next fed to classifiers for recognition and verification of signatures. We have compared SVM and HMM based results in this paper.

The rest of the paper is organized as follows. Section 2 details the related works. In Sect. 3 we discuss about the data collection. Section 4 details the preprocessing techniques used and the proposed approaches of feature extraction methods. Section 5 details the experimental results. Finally, conclusion of the paper is given in Sect. 6.

## 2 Literature Survey

To the best of our knowledge, no study is available for online handwritten signature recognition and verification in Indic scripts. Some of the related studies available in non-Indic scripts are discussed below.

Plamondon et al. [3] reported an online handwritten signature verification scheme where signature features related to temporal and spatial aspects of the signature, are extracted. Several methods have been proposed for using local features in signature verification [4]. The most popular method uses elastic matching concept by Dynamic Warping (DW) [5, 6]. In the literature, several hundreds of parameters have been proposed for signature recognition and verification. Among these, the parameters like position, displacement, speed, acceleration [7, 8], number of pen ups and pen downs [8], pen down time ratio [7], Wavelet transform [9], Fourier transform [10] have been extensively used. Dimauro et al. [11] proposed a function-based approach where online signatures are analysed using local properties based on time sequences. In this approach, a signature is characterized by a time function [11]. In general, better performances are obtained from function-based approaches than the parameter-based approach but time-consuming matching/comparison procedures are involved in function-based approach. However, another study [12] shows that both parametric and function-based approaches are equally effective. During matching, the authenticity of test signatures are validated by comparing the features of test signatures against the model created from the training set. The matching techniques based on Dynamic time warping (DTW), Hidden Markov Model (HMM), Support vector machine (SVM) and Neural Networks (NN) are commonly used.

## 3 Devanagari Script and Online Data Collection

Devanagari (or simply Nagari), the script used to write languages such as Sanskrit, Hindi, Nepali, Marathi, Konkani and many others. Generally, in Devanagari script, words or signatures are written from left to right and the concept of upper-lower case alphabet is absent in this script. Most of the words or signatures of Devanagari script have a horizontal line (*shirorekha*) at the upper part. Figure 1 shows two different online handwritten signatures in Devanagari script where *shirorekha* is drawn in the upper part of both the signatures.

Online data acquisition captures the trajectory and strokes of signatures. In online data collection, the rate of sampling of each stroke remains fixed for all signature samples. As a consequence, the number of points in the series of co-ordinates for a particular sample does not remain fixed and depends on the time taken to write the sample on the pad.

For our data collection, a total of 100 native Hindi writers belonging to different age groups contributed handwritten signature samples. Each writer was prompted to provide five genuine samples of each signature in Devanagari script. So, a total of 500 samples have been collected for each genuine signature in Devanagari script. The training and testing data for genuine signatures are in 4:1 ratio. Each writer was also prompted to provide five forged signatures of five other people. So, a total of 500 samples have been collected of forged signatures.

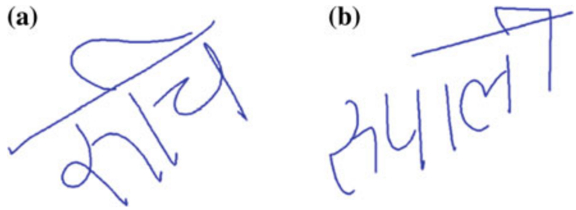


**Fig. 1** Two different online handwritten signatures in Devanagari script

## 4 Feature Extraction

Before extracting the features from strokes, a set of preprocessing tasks is performed on the raw data collected for each signature sample. Preprocessing includes several steps like *interpolation*, *smoothing*, *resampling* and *size normalization* [13]. Figure 2 shows the images of one online handwritten signature in Devanagari script before and after smoothing. The detailed discussion about these preprocessing steps may be found in [13].

During feature extraction phase, the features that will be able to distinguish one signature from another, are extracted. The feature extractions are done on the entire signature image, irrespective of the number of strokes it contains. We discuss below the proposed zone-based feature extraction approach for signature recognition and verification.

**Zone wise Slopes of Dominant Points (ZSDP)**: The whole signature image is divided into a number of local zones of $r$ rows $\times$ $c$ columns. But, instead of directly local feature extraction, we divide the portion of the strokes lying in each zone into dominant points. These dominant points are those points where the online stroke changes its slope drastically. In order to extract this feature, at first, *slopes* are calculated between two consecutive points for the portion of the trajectory lying in each local zone. The *slope* angles are quantized uniformly into 8 levels. Let, the resultant quantized slope vector for any particular zone is $Q = \{q_1, q_2, \ldots, q_n)$. Formally, a point, $p_i$ is said to be a dominant point if the following condition is satisfied:

$$|q_{i+1} - q_i| \, \% \, k \geq CT$$

where, CT is *Curvature Threshold* and % is *modulo* operator. Here, $k = 8$ is used for modulus operations because each element $q_i$ of the quantized slope vector can take any value from 0, …, 7. By default, the first and last point of a stroke are considered as dominant points. Figure 3 illustrates this concept. It is noted that, when CT = 0, it contains all points as dominant points. The number of dominant points keeps decreasing with increasing CT. When CT is more than 3, very few dominant points remain.

Next, the slope angles between consecutive dominant points are calculated in each zone. The slope angles are quantized uniformly into 8 levels. If the resultant angular values of *slope* lie between $0^\circ$ and $45^\circ$ then the corresponding dominant point is placed in bin1, if the values lie between $46^\circ$ and $90^\circ$ it is placed in bin2, and

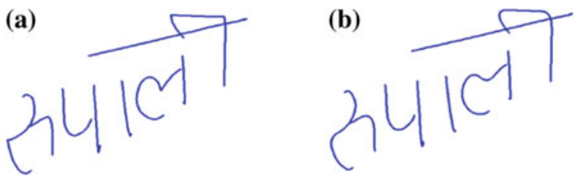

**Fig. 2** Example of one online handwritten signature in devanagari script **a** After interpolation but before smoothing. **b** After smoothing the trajectories of strokes

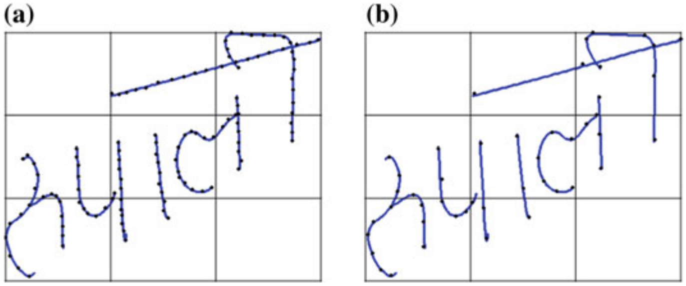

**Fig. 3** Dominant points of different strokes of an online handwritten signature in devanagari script for different threshold values a) CT = 0, b) CT = 1

so on. We have tested with other bin divisions, but the one using pi/4 gives the best accuracy. The histograms of feature values are normalized and we get 8 dimensional feature vector for each zone. So, the total dimension for 9 zones is $8 \times 9 = 72$.

## 5 Experimental Results and Discussion

Support Vector Machine (SVM) and Hidden Markov Model (HMM) classifiers are used for our online signature recognition and verification system. Support Vector Machine (SVM) has been applied successfully for pattern recognition and regression tasks [14, 15].

We apply Hidden Markov Model (HMM) based stochastic sequential classifier for recognizing and verifying online signatures. The HMM is used because of its capability to model sequential dependencies [16]. HMM classifier has been implemented through HTK toolkit [17].

The experimental testing of the proposed approach was carried out using online handwritten Devanagari genuine and forged signatures. The feature vectors of genuine signatures are used to build the training set which is used to build a model for validating the authenticity of test signatures. Two separate testing sets are created—one for genuine signatures and another for forged signatures.

### 5.1 *Signature Recognition Result*

**Results using SVM**: Using the current approach, the system has been tested using different kernels of SVM and by dividing the entire signature image into different zones. Using this approach, best accuracy is obtained using the combination of 16 zone division, CT = 2 and linear kernel of SVM. The detailed result analysis, using ZSDP approach, is shown in Table 1.

**Table 1** Signature recognition results using SVM with different kernels for ZSDP approach

| *ZSDP* | | | | |
|---|---|---|---|---|
| Zones | CT | RBF kernel (%) | Linear kernel (%) | Polynomial kernel (%) |
| 9 (3 × 3) | 2 | 87.03 | 92.57 | 88.23 |
| 9 (3 × 3) | 3 | 84.89 | 89.89 | 85.17 |
| 9 (3 × 3) | 4 | 81.85 | 86.85 | 82.11 |
| 16 (4 × 4) | 2 | **93.42** | **98.36** | **94.73** |
| 16 (4 × 4) | 3 | 90.23 | 95.23 | 91.47 |
| 16 (4 × 4) | 4 | 87.76 | 92.76 | 88.20 |

**Table 2** Signature recognition results using HMM for ZSDP approach

| HMM states | Gaussian mixture | *ZSDP (%)* |
|---|---|---|
| 3 | 16 | 84.58 |
| 4 | 16 | 70.21 |
| **3** | **32** | **88.23** |
| 4 | 32 | 74.59 |
| 3 | 64 | 88.23 |
| 4 | 64 | 74.59 |

**Results using HMM**: The testing datasets for HMM based experimentation are same as used in SVM based experimentation. Table 2 shows the recognition accuracies using *ZSDP* approach. In our experiment, we have tried different Gaussian mixtures and state number combinations. We noted that with 32 Gaussian mixtures and 3 states, HMM provided the maximum accuracies. Figure 4 shows the signature recognition results using ZSDP approach based on different top choices for both SVM and HMM.

## 5.2 Signature Verification Result

To validate the authenticity of each genuine signature, forged signatures are used as test samples. For signature verification, generally two different measurement techniques are employed to measure the performance of the verification system—False Acceptance Rate (FAR) and False Rejection Rate (FRR). The first one indicates the rate of accepting forgeries as genuine signatures and the second one indicates the rate of rejecting forged signatures. For a good signature verification system, the value of FAR should be very low and FRR should be high. Table 3 shows the signature verification results through FAR and FRR.

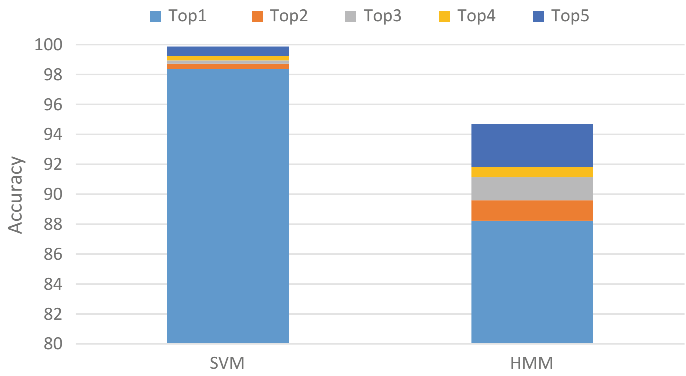


**Fig. 4** Signature recognition results for ZSDP approach based on different Top choices using SVM and HMM

**Table 3** Signature verification results using ZSDP approach

| Classifier | FAR (%) | FRR (%) | Accuracy (%) |
|---|---|---|---|
| SVM | 2.89 | 97.11 | 97.11 |
| HMM | 6.70 | 93.30 | 93.30 |

### *5.3 Comparative Analysis*

Among the existing studies in the literature, to the best of our knowledge, no work exists on online handwritten signature verification system in Devanagari script. So, the present work cannot be compared with any of the existing studies.

## 6 Conclusion

In this paper, we have described one approach of feature extraction for online handwritten signature recognition and verification in Devanagari script. In our dataset we considered five samples each for signatures of 100 different persons in Devanagari script. The experimental evaluation of the proposed approach yields encouraging results. This work will be helpful for the research towards online recognition and verification of handwritten signatures of other Indian scripts as well as for Devanagari.

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