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A REVIEW ON HANDWRITTEN DEVNAGARI NUMERALS RECOGNITION USING SUPPORT VECTOR MACHINE

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***Abstract*— Handwriting has continued to persist as a mean of communication and recording information in day-to-day life even with the invention of new technologies. Natural handwriting is one of the easiest ways of information exchange between a human and a computer. Handwriting recognition has attracted many researchers across the world since many years. Recognition of online handwritten Devanagari numerals is a goal of many research efforts in the pattern recognition field The main goal of the work is the recognition of online hand written Devanagari numerals using support vector machine. In the data collection phase, co-ordinate points of the input handwritten numeral are collected as the numeral written; various algorithms for pre-processing are applied for normalizing, resampling and interpolating missing points, smoothing and slant correction. Two low-level features i.e. direction angle and curvature are extracted from the pre processed data. These features along with the x and y coordinates of the input handwritten character are stored in a .csv file and fed directly to the recognition phase. Recognition is done using four kernel functions of SVM by partitioning the data into different schemes. The recognition accuracies are obtained on different schemes of data using the four kernel functions of SVM for each scheme.**

Keywords— Data Collection, Pre-processing, Feature Extraction, SVM, Handwriting Recognition.

I. INTRODUCTION

The primary modes of data input between a user and a computer are still the conventional input devices such as keyboards and mouse. These devices have some limitations when compared to the input through natural handwriting. For scripts such as Chinese and Japanese which have a very large alphabet set and due to complex typing nature of script such as Devanagari and Gurumukhi, it becomes difficult to input data to the computer through the conventional input devices. Natural handwriting is one of the easiest ways to exchange information between a human and a computer. Thus, the Devnagari numerical recognition field has better communication between the user and the computer by using SVM

SVM stands for Support Vector Machine and this method of recognition is gaining immense popularity now-a-days. SVM classifier gives better results as compared to the other classifiers for the handwritten numeral recognition of Kannada script in [3]. In [6], SVM approach is used to recognize strokes in Telugu script. The set of strokes are segmented into subsets based on the relative position of the stroke in a character. An SVM based classifier is built for recognition of strokes in each subset. A rule based approach is used to recognize a character from the sequence of stroke classes given by the stroke classifier. SVM is a new classifier that is used in many pattern recognition applications with good generalization performance. SVM has been used in recent years as an alternative to popular methods such as neural network.

II. PHASES OF ONLINE HANDWRITING RECOGNITION SYSTEM

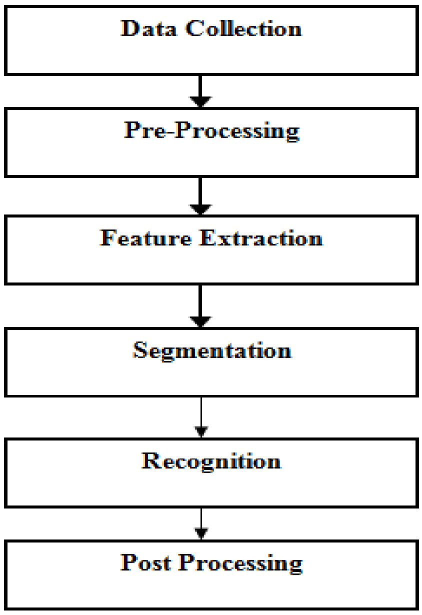


Fig.1: Flow of Numerical Recognition System

These techniques were based on electromagnetic/electrostatic and pressure sensitive techniques the combination of digitizer and display in the same surface has become very common since many years. There is an established procedure to recognize online handwritten data which includes the following phases or components: Data collection, pre-processing, feature extraction, segmentation, recognition and post processing.

Figure 2. Sample Devnagari Numerals from ISI database.

III. METHODOLOGY

A. Data collection: -

Data collection is the first phase of online handwriting recognition that collects the sequence of co-ordinate points of the moving pen. A transducer is required to capture the handwriting as it is written. The most common devices used for this purpose are electronic tablets or digitizers. A digital pen is used for writing on these devices. Digital pen is also sometimes called as "stylus". A typical digital pen includes two actions namely Pen Down and Pen Up. The connected parts of the pen trace between Pen Down and Pen Up is referred to as a stroke. It is considered as a smallest unit in handwriting recognition. All the unique strokes of a script are manually identified and given unique labels. Stroke is basically a smallest physically identifiable unit in online handwriting. The pen traces are sampled at a constant rate and thus, these pen traces are evenly distributed in time but not in space. The most common examples of electronic tablet or digitizers include Personal Digital assistant (PDA), tablet PC, cross pad (or pen tablet) and a digi memo. A digimemois a portable device which digitally captures and stores the ink written on ordinary paper using a digital pen and pad, thus providing a natural interface for collecting handwritten data samples.

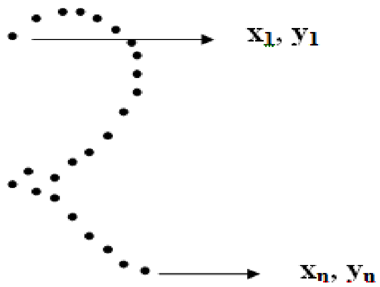


Figure 3. Points of pen movement collected while writing

B. Pre-Processing:-

While inputting data through a pen on the digitizer tablets, there may be certain noise distortions present in the input text due to some limitations, which may make the recognition of input difficult. Irregular size, missing points due to fast movement of the pen, uneven distances of points from neighboring positions are various forms of noise and distortions. These noise and distortions present in the input text are removed in the second phase of online handwriting recognition i.e. pre-processing phase.

The pre processing phase includes five common steps namely:

- size normalization and centering
- interpolating missing points
- smoothing
- Slant correction.
- resampling of points

This problem of bend or slant in handwriting is solved using the slant correction methods. Duplicate points are redundant and do not contain any information. Thus, these are removed from the captured ink. Resempling of points is done to fix the number of points to be used for recognition and the fixed points are selected in such a way that the original character can be retraced from those points.

C. Feature Extraction:-

Feature extraction is a very crucial step as the success of a recognition system is often attributed to a good feature extraction method. The feature extractor determines which properties of the preprocessed data are most meaningful and should be used in further stages. Vertical position of a point, curvature, Pen Up/Pen Down, writing direction, aspect, slope are amongst the various features extracted in [5]. In [6], six scalar features are extracted from each sub stroke.In the present dissertation, two low level features have been extracted namely:

1. **Direction Angles**

Direction angle is the angle that the two successive coordinate points of the input handwritten character make with the x-axis in anti-clockwise direction. After theresampling done on the input character, the number of coordinate points is fixed to 64.These 64 resample points are then used to calculate the direction angles. The direction angles are calculated from point 1 to point 2, then from point 2 to point 3 and so on. The angle for the first point of stroke sample has been considered as zero because of the non availability of previous consecutive point.

2. Curvature

Curvature is found by drawing a curve between three points and then drawing a curve joining those three points. Radius of curvature value of that curve is then found using the above mentioned formula. Curvature is found for points taken in triplet e.g. 1, 2 and 3; then 2, 3 and 4; and so on. Total of 64 curvature values are obtained for the pre processed64 resample points. A value of 1000000 is assigned to the curvature in case the line joining the three points is not a curve but a straight line. The curvature for the first poin tof stroke sample has been considered as zero because of the non-availability of previous consecutive point.

D. Segmentation:-

Segmentation is the phase in which data is represented at character or stroke level so that nature of each character or stroke can be studied individually. Segmentation is classified into two categories [8] namely:

- External Segmentation
- Internal Segmentation.

RECOGNITION OF NUMERALS:-

The process has been implemented on the handwritten Devanagari numeral data collected in this work. Numerals are written by ten writers. Devanagari numeral system consists of a set of ten numeral symbols .Each writer was asked to write ten samples of each numeral. Thus, 1000 samples in all are created during this work. The co-ordinate points of the input handwritten character are collected as the character is written. The input handwritten character then undergoes pre-processing and the pre-processing phase resample points are obtained. These resample points are then fed to the feature extraction phase where two low level features i.e. direction angle and curvature are extracted. Together all this data i.e. x, y coordinate points, direction angle and curvature for each point of each character are stored in .csv file. The data from this file is then fed to the next phase i.e. recognition phase. In the second level of experimentation, the data that is fed into the recognition phase is partitioned into the following six schemes:-

SCHEME 1: x, y, direction angle, curvature

SCHEME 2: x, y and direction angle

SCHEME 3: x, y and curvature

SCHEME 4: direction angle and curvature

SCHEME 5: direction angle only

SCHEME 6: curvature only

F. SVM KERNELS

Linear kernel: Linear SVM is linearly scalable with the size of the training data set. It in by the following formula:

$$k(x, y) = x^* y$$

Where, k(x, y) is the kernel function

Polynomial kernel: It is a non-stationary kernel which is well suited for problems where the training data is normalized. It is given by the following formula

$$k(x, y) = (\alpha\, x^T y = c)^d$$

Where, α is the slope, c is the constant term and d is the polynomial degree.

RBF kernel: It is defined on the interval [-1, 1] and is given by the following formula

$$K(x, y) = \exp(-\| x - y \|^2 / 2\sigma^2)$$

Sigmoid kernel: With gain κ and offset ϴ , the formula for a sigmoid kernel is given by:

$$k(x, y) = \tanh(\kappa(x.y) + \theta)$$

In feature extraction, the edges of the segmented and morphologically filtered image are found. Canny edge detector algorithm is used to find the edges of the image. Then a contour tracking algorithm is applied to track the contour.

IV. PRELIMINARY WORK ON FEATURE EXTRACTION TECHNIQUES

In this section, we introduce various feature extraction techniques for Gurumukhi script. This section is divided into 2 parts: (i) handwritten character (ii) handwritten numeral. In this survey, we only review the offline handwritten characters/numerals recognition.

HANDWRITTEN CHARACTER RECOGNITION

The major difficulty in handwritten character recognition is the variability of writing styles between two different writers. In this paper, they proposed two feature extraction techniques namely parabola fitting and power curve fitting techniques. They also analyzed the performance of other techniques like zoning, diagonal, directional, gradient and chain code features. The classifiers that are used namely Support vector machine and k-NN classifiers with 3 flavors, i.e., SVM with linear kernel, SVM with polynomial kernel and SVM with RBF kernel. The system achieves a recognition accuracy of 98.10 and 97.14% using k-NN and SVM classifiers [1] [8].

In this paper, they proposed an isolated handwritten Gurumukhi character recognition system. They used Gabor filter based method for extracting the features. For dataset, 200 samples of 35 characters are collected from different persons. SVM classifier is used for classification purpose. The maximum accuracy achieved is 94.29% with purposed method [2]. Table shows an overview of various feature extraction techniques & classifiers for handwritten character recognition

SELECTED RECOGNITION RESULTS FROM LITERATURE OF ONLINE HANDWRITING RECOGNITION SYSTEM

A. Recognition using Gabor filter

A two dimensional Gabor filter is a linear filter that acts as band pass spatial filter with the ability to tune to certain orientation and spatial frequency. Its Impulse Response Function (IRF) also known as carrier is a complex sinusoid which is modulated by an elliptical shaped Gaussian envelope. Its computation in spatial domain is given by:

$$g(x,y;f_0,\theta) = \frac{1}{2\pi\sigma_x\sigma_y}.\exp^{-\left[\frac{x'^2}{2\sigma x^2}+\frac{y'^2}{2\sigma y^2}\right]}.\exp^{i2\pi(u_0x+v_0y)}$$

$$= \frac{1}{2\pi\sigma_x\sigma_y}.\exp^{-\left[\frac{x'^2}{2\sigma x^2}+\frac{y'^2}{2\sigma y^2}\right]}.\exp^{(i2\pi f_0 x')}$$

$$x' = x\cos\emptyset + y\sin\emptyset \text{ and } y' = -x\sin\emptyset + y\cos\emptyset$$
$$u_0 = f_0\cos\emptyset \text{ and } v_0 = f_0\sin\emptyset$$

where (x, y) are the spatial co-ordinates, f0 is the centre frequency (where the filter yields the greatest response), θ is the orientation of sinusoidal plane wave, x' and y' are rotation co-ordinates, σx and σy are the width or spread of the elliptical Gaussian envelope along x and y axis respectively, (u0, v0) are the centre spatial frequencies of the sinusoidal wave in Cartesian co-ordinates, (f0, θ) are their corresponding counterpart frequency magnitude (f0 = sqrt (u02 + v02)) and direction (θ = tan-1 (u0/vo)) .

When expressed in polar co-ordinates. The complex sinusoid has even-symmetric component (real part) and odd-symmetric component (imaginary part). These are separate real functions that independently exist in the real and the imaginary part of the complex sinusoid function.[16]

$$g_{even}(x,y;f_0,\theta) = \frac{1}{2\pi\sigma_x\sigma_y}.\exp^{-\left[\frac{x'^2}{2\sigma x^2}+\frac{y'^2}{2\sigma y^2}\right]}.\cos 2\pi f_0 x'$$

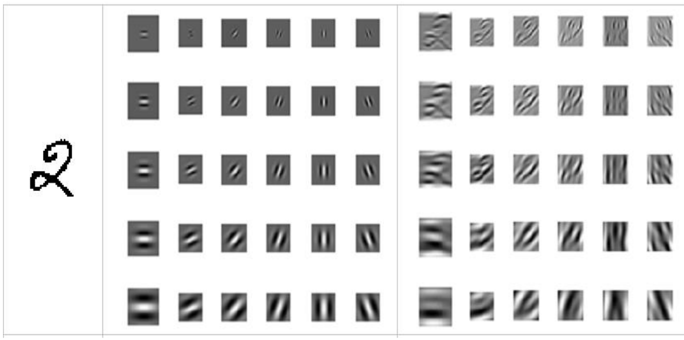
$$g_{odd}(x,y;f_0,\theta) = \frac{1}{2\pi\sigma_x\sigma_y}.\exp^{-\left[\frac{x'^2}{2\sigma x^2}+\frac{y'^2}{2\sigma y^2}\right]}.\sin 2\pi f_0 x'$$

In wavelet framework, the parameters of the Gabor filters of multiple scales are interrelated: Frequencies are related logarithmically, the Gaussian envelope has a constant aspect ratio. and its scale is inversely proportional to the oscillatory frequency. Based on the above constraints, and θ are the only two free parameters.

The Figure 3 is convolved with each of the Even and Odd Gabor filter in the filter bank. Let M x N be the size of the Gabor filter g. The convolution of the image at sampling point (x, y) for the corresponding filter at (f0 θ) is given by:

G (x, y; f0, θ) = I (x, y) *g (x, y; f0, θ)

Author(s)	Method	Dataset	Recognition /Error rate
Singh. S., et al. [1]	**SVM** with RBF Kernel Geber filter	Handwritten Characters	94.29%
Scott D. Connell et al.[2] (2000)	HMM and k-NN classifiers	Unconstrained Devanagari characters with writer independent system	86.5%
Kumar M et al. [3]	k-NN classifier	(A-Z) characters and (a-z) characters;	94.12%.
Kumar M et al. [4]	SVM, k-NN classifiers	Handwritten characters	98.10 97.14%



Devnagari Numeral Gabor Filter – Convolution: G

Bank: f = 5, θ = 8, size = 31x31. = g(x, y ; f, θ) * Image (x,y)

B. Hidden Markow Model

In this paper, the problem of handwriting recognition given a large vocabulary and unconstrained handwriting is addressed. The basic problem we have to solve is this: Having multiple character class models to cope with unconstrained handwriting, how does one make use of these models and accommodate them into a lexicondrivenrecognition approach where a large vocabulary is employed? In this paper, we focus our attention on the problem of matching a sequence of observations generated from high-level features extracted from words andstatistical models of characters (HMMs)in an efficient manner.They presented a paper in which a grading system for Punjabi writers based on offline handwritten Gurumukhi characters recognition. They proposed four feature extraction methods, namely, zoning, diagonal, directional, intersection and open end points and Zernike moments feature. For classification, k-NN, HMM and Bayesian classifiers are used. They also compare the handwriting of one writer with other writers. This approach can also be extended for other Indian scripts such as Bengali, Tamil and Devanagri [4]

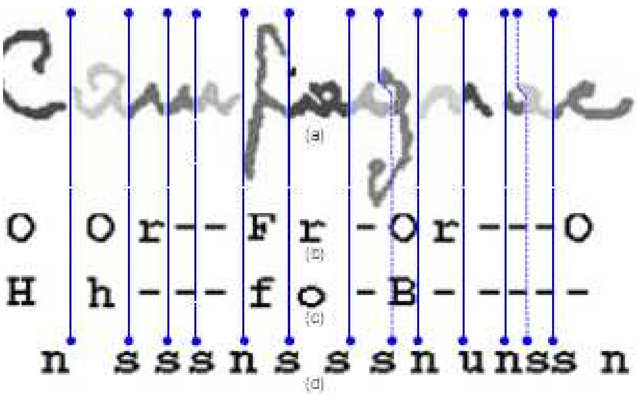


Fig. 4. a Segmentation of a word into characters or pseudo characters. b.Sequence of global features. c Sequence of bidimensional contour transition histogram features. d Sequence of segmentation features.[20][21]

Before segmentation the input images are preprocessed to get rid of information that is not meaningful to recognition and that may lead to dependence between observations. Following the segmentation, two sequences of high-level features are extracted from the segments to form an observation sequence. During training, since only the word labels are available, word models are built up of the concatenation of the appropriate character models and the training algorithm decides itself what the optimal segmentation might be. Recognition is carried out by a lexicon-driven decoding algorithm where each word in the lexicon is modeled by a "super-HMM" created by concatenating character HMMs. The decoding algorithm finds the N best word hypotheses that have the highest likelihood given the observation sequence .In the following sections, we provide a brief description of the main components of the handwriting recognition system.

C. k-NN classifier

They have been presented a paper on offline handwritten Gurumukhi character recognition system. They proposed two feature extraction techniques namely diagonal features and transition features with k-NN classifier. When they have used the diagonal features with k-NN classifier, the maximum recognition accuracy achieved 94.12%. The recognition accuracy can be improved by considering a large dataset of characters for training the classifiers . In this paper, they has been used a 48*48 pixels normalized image and created 64 (8*8) zones and used zoning densities of these zones as features. The values in feature vector are normalized in the range 0 to 1. They observed 73.02% highest accuracy with SVM kernel with Poly. Kernel.[3]

Conclusion

In this paper the the main goal is online handwritten Devanagari numeral recognition system. This thesis describes the pre-processing, feature extraction and the recognition phase. Pre-processing and feature extraction are done prior to recognition to increase the efficiency of the character recognition system. Direction angle and curvature are the two features extracted. Recognition is done using four kernel functions of SVM by dividing the data into six schemes depending on the features extracted. Good recognition accuracies have been obtained for all the six schemes and the kernels. Results obtained are reasonably good when the linear kernel is used as compared to the other kernels. The highest accuracy shown by the linear kernel is 98.900%. The results also prove that direction angle and curvature are two very important features and enhance the recognition process. The two features showed good results even when used individually for character recognition especially the direction angles. In this paper, we have reported the various work done on Gurumukhi script. We have organized the review around work have done on handwritten characters/numerals. In this review paper, compared the various feature extraction techniques, classifiers & different datasets which are used in Gurumukhi script for improving the recognition performance.[22]

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