Indian Journal of Science and Technology, *Vol 8(27), DOI: 10.17485/ijst/2015/v8i27/81856, October 2015*

ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645

Recognition of Devnagari Numerals using Gabor Filter

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Abstract

Various feature extraction techniques are proposed in literature that can be utilized for recognition purpose in different applications. Gabor Filter is one such well known technique that has the capability to capture image characteristics both in frequency and time domain in parallel. This paper presents an offline Devnagari handwritten numeral recognition system using the famous feature extraction technique of Gabor filter. The effort is to explore the Gabor filter discrimination capabilities and find the optimum feature computation vector in order to improve the recognition rate. Three filter sizes 7 x 7, 19 x 19 and 31 x 31 are experimented with to find the optimal filter size for the given case study. The Standard Benchmark handwritten Devnagari numeral database provided by ISI, Kolkata is used as the training and testing dataset. The original grayscale database images are binarized and normalized to 32 x 32 sizes before feature extraction. The classification is done using the Nearest Neighbor and Support Vector Machine. The maximum recognition accuracy achieved is 98.06%.

Keywords: Devnagari Characters, Gabor Filter, Offline Handwritten Numeral Recognition, SVM

1. Introduction

Gabor filters have been widely used in Pattern Recognition, Computer Vision and Document Analysis applications. With their insemination from the classic paper[1], they have been successfully applied in different applications of Image Processing like texture analysis, number plate recognition, object tracking and biometric systems of iris, face, palm and finger-print recognition. In Optical Character Recognition (OCR), they have been applied in multi-script segmentation and character recognition. The visual properties like optimal spatial localization, orientation selectivity and robustness against noise have made Gabor filters useful in all these spheres.

Devnagari Script has descended from Bramhi script and is the most popular script in India. It is used to write many languages like Sanskrit, Hindi, Marathi, Pahari, Bhojpuri, Bhili, Magahi, Maithili, Nepali and Mundri. The Basic Character set includes 14 vowels and 33 consonants and Phonetic-alphabetic system is adopted. In word formation, the vowels are written as diacritic marks on the immediately preceding consonant making the script two dimensional. The position of diacritic mark and the point of attachment depend entirely on the shape of the preceding consonant. Moreover the presence of half characters, multiple shapes of one character, formation of new character shape due to different character combination makes the recognition task more difficult and complex.

In 1946, D. Gabor[1] gave a new method for analyzing signal in which time and frequency played symmetric part. One dimensional Gabor filter which is multiplication of sinusoidal wave with a Gaussian function was originally introduced by him. Daugman[2] extended one dimensional Gabor filter to two dimensional filter family and presented evidence of their ability to simulate the receptive field profiles of simple cells in mammalian visual cortex. Ilonen et al.[3] discussed efficient computation of Gabor filters. Urolagin et al.[4] utilized Gabor filter for illumination invariant printed numeral recognition. Rani

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et al.[5] presented Gabor feature based script identification within a Bilingual / Trilingual document. Hu et al.[6] did low resolution gray character recognition for vehicle license plate using Dominant orientation matrix as Gabor feature. They experimented on 7 x 7, 9 x 9, 11 x 11, 15 x 15 dimensions and gave maximum 96.66% recognition accuracy. Hamamoto et al.[7] used the feature for recognition of Hand-printed Chinese characters. They experimented on ETL-8 character set and reported minimum error rate of 2.4%. Hamamoto et al.[8] also utilized the feature for recognition of Hand-written numerals using ETL-1 character set reporting 2.51% error rate. Liu et al.[9] applied Gabor features for character recognition on MNIST and CENPARMI handwritten digit database and achieved 99.47% and 98.95% accuracy respectively. Wang et al.[10] used Gabor filter and reported the recognition accuracy on low quality machine-printed Chinese character (99.87%), cursive handwritten Chinese characters (98.77%) and Handwritten numerals (MNIST dataset) (with MQDF classifier) (0.87% error rate). Singh et el.[11,12] applied Gabor filter to recognize handwritten Gurumukhi characters getting 94.29% accuracy and handwritten Gurumukhi Numeral recognition getting 99.53% accuracy.

The pioneer development of Standard Benchmark Handwritten databases for Devnagari and Bangla scripts is done by Bhattacharya and Chaudhuri[13]. The numeral recognition work reported using ISI Devnagari Numeral Standard Database is as follows. Pal et al.[14] used 64 and 400 dimensional features with MQDF classifier and attained 99.56% accuracy. Bhattacharya and Chaudhuri[13] applied Wavelet based technique and Chain code histogram using MLP classifier achieving 99.27% accuracy. Singh et al.[15] performed recursive subdivision of numeral image with SVM, K-NN and Quadratic classifier reporting 98.98% accuracy. Aggarwal et al.[16] applied Gradient feature using Sobel operator with SVM classifier achieving accuracy of 99.6%.

2. Recognition using Gabor Filter

2.1 Feature Extraction

2.1.1 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:

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

$$=\frac{1}{2\pi\sigma_x\sigma_y}.\exp^{-\left[\frac{x'^2}{2\sigma x^2}+\frac{y'^2}{2\sigma y^2}\right]}.\exp^{(i2\pi f_0x')} \quad (1)$$

x' = x cos Ø + y sin Ø and y' = - x sin Ø + y cos Ø

$u_0 = f_0 \cos Ø$ and $v_0 = f_0 \sin Ø$

where (x, y) are the spatial co-ordinates, f_0 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, σ_x and σ_y are the width or spread of the elliptical Gaussian envelope along x and y axis respectively, (u_0, v_0) are the centre spatial frequencies of the sinusoidal wave in Cartesian co-ordinates, (f_0, θ) are their corresponding counterpart frequency magnitude ($f_0 = \text{sqrt}(u_0^2 + v_0^2)$) and direction ($\theta = \tan^{-1}(u_0/v_o)$) 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.

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

$$g_{odd}(x,y;f_0,\theta)=\frac{1}{2\pi\sigma_x\sigma_y}.\exp^{-\left[\frac{x'^2}{2\sigma x^2}+\frac{y'^2}{2\sigma y^2}\right]}.\sin 2\pi f_0 x' \quad (3)$$

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 $\left(\alpha=\frac{\sigma_y}{\sigma_x}\right)$ and its scale is inversely proportional to the oscillatory frequency. Based on the above constraints, and θ are the only two free parameters[9].

2.1.2 Multi-Resolution Gabor Features

A filter bank is a combination of Gabor filters calculated at different scales and orientations. It is generally employed to compute the Gabor feature. It helps to recognize the object irrespective of its geometric transformation[3]. The process of Gabor filter computation is illustrated in Figure 1.

Frequency: The oscillating frequency is calculated by:

$$f_j = v^{-j} f_{\max}, j = \{0, \ldots\ldots, n-1\}, v \in \left\{\sqrt{2}, 2, 2\sqrt{2}\right\} \qquad (4)$$

where ν is the scaling factor whose value is selected from the set {√2 (0.5 octave), 2 (1 octave), 2 √2 (1.5 octave)} and n is the total number of frequencies.

Orientation: The different Orientation values selected are equally spaced between the range [0, π] and calculated using formula

$$\theta_l = \frac{l\pi}{n}, 1 = \{0, \ldots\ldots, n-1\} \qquad (5)$$

where n = total number of orientations. The responses in range [π, 2π] are complex conjugate responses on real valued inputs and hence left.

2.1.3 Gabor Feature Computation

The Figure 1 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 (f_0 θ) is given by:

$$G\,(x, y; f_0, \theta) = I\,(x, y)\ {}^*g\,(x, y; f_0, \theta) \qquad (6)$$

The Convolution operation in spatial domain is done using:

$$G(x, y; f_0, \theta) = \sum_{X=\left\lfloor x-\frac{M}{2}\right\rfloor}^{\left\lceil x+\frac{M}{2}\right\rceil} \sum_{Y=\left\lfloor y-\frac{N}{2}\right\rfloor}^{\left\lceil y+\frac{N}{2}\right\rceil} I(x, y).g\left(X-x, Y-y; f_0, \theta\right) \qquad (7)$$

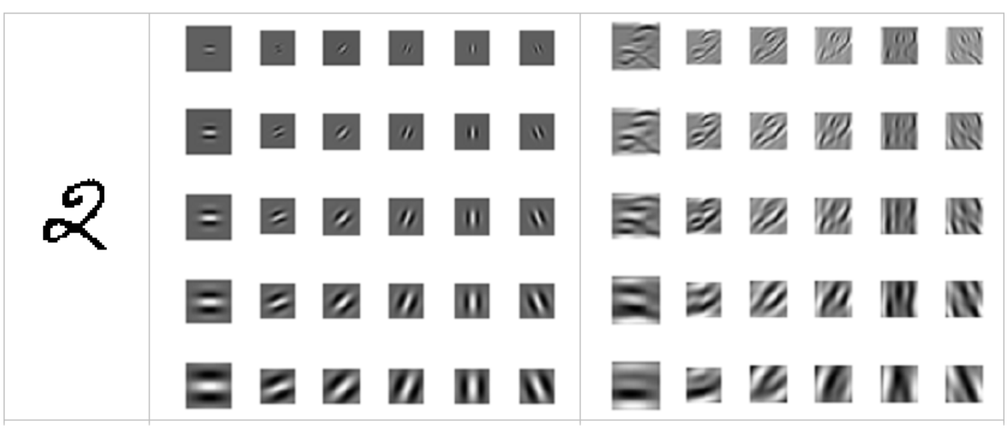
The resultant matrix after convolution is of the size of the image. Further, the Mean and Standard Deviation is computed for each of the convolved matrix G_{even} and G_{odd} which are utilized as features.

2.2 Classification

Classification is the stage after feature extraction in which the feature vector obtained for unknown test-data are matched with that of known training-data. The unknown test-data is assigned the class of that known training-data which has the closest similarity.

2.2.1 Nearest Neighbor Classifier

The divergence between the feature-vector of test-data and the feature-vector of each of the training-data is calculated using some distance metric. The Euclidean distance is used as distance metric in present work. The Euclidean distance between an input feature vector X and a library feature vector C is given by $D = \sqrt{\sum_{i=1}^{N}(C_i - X_i)^2}$ where C_i is the i^{th} library feature, X_i is the i^{th} input feature and N is the number of features used for classification. The test-data is labeled with the class of that training-data which results in the minimum distance value.



Devnagari Numeral

Gabor Filter - Bank: f = 5, θ = 8, size = 31x31

Convolution: G = g(x, y ; f, θ) * Image (x,y)

Figure 1. Gabor filters computation process

2.2.2 Support Vector Machine

SVM are a set of related supervised learning methods used for classification and regression. It utilizes the separating hyper-plane to find the optimal one which groups the unknown test data using the known (labeled) training data into clusters. Though it is designed for the binary class problems, it can be extended to multiclass dataset using one against the rest approach. Presently, it is used to solve the multiclass problem using LIBSVM 2.8.2 classifier tool[17,18] with Linear, Radial Basis Function (Gaussian) and Polynomial kernel.

3. Experimentation and Result Discussion

3.1 Database Used

The Standard Benchmark Handwritten Devnagari Numeral Database provided by CVPR Unit, ISI, and Kolkata is used for experimentation purpose[13]. It is a collection of the grayscale tiff images of isolated Handwritten Devnagari Numerals. Some samples of the collection of the ISI database are shown in Figure 2 and the size of the database is given in Table 1.

Table 1. The size of database

Devnagari Numerals	Training Data Size	Testing Data size
0	2044	369
1	1996	378
2	2053	378
3	1931	377
4	2072	376
5	1919	378
6	1961	374
7	1927	378
8	2021	377
9	1874	378
Total	**19798**	**3763**

3.2 Pre-Processing

The images are first binarized using Otsu method and then normalized to 32 x 32 sizes to standardize input before feature extraction. The database images are of different sizes and feature extraction using Gabor filter results in image size vector. Size normalization gives uniform size to the input data before feature extraction leading to equal size Gabor feature vector in result. No other preprocessing technique is applied.

Figure 2. Sample Devnagari Numerals from ISI database.

3.3 Filter Size

Three filter sizes- small (7 x 7), medium (19 x 19) and near image size (31 x 31) were experimented with to find the optimum filter size to minimize computation time and cost. As Gabor filter is a linear filter, odd filter sizes were opted for the correct alignment on image for convolution purpose.

3.4 Filter-Bank

Multi-resolution Gabor features are extracted using the responses calculated with Gabor filters at different scales (frequency levels) and orientations (θ).

3.5 Frequency Selection

The frequency range selected is as per the formula- frequency = 1/(2*W), where W is the stroke-width, used by Wang et al[10]. The stroke-width (W) is assumed as 2-pixel to 8-pixel for our handwritten numeral set. Hence the frequency is 0.25 and 0.0625 for 2-pixels and 8-pixels width respectively. To cover the maximum intermediate values, we have used the minimum scaling factor, $\nu = \sqrt{2}$ (half octave spacing). Thus the desired frequencies obtained using the formula (4) with $f_{max} = 0.25$ and n = 5 are {0.25, 0.1767, 0.125, 0.8838, 0.0625}.

3.6 Orientation Selection

Keeping in view the curved nature shapes of Devnagari Numerals, 8 different orientations are taken for reasonable direction spread. The orientations are calculated through formula (5) with n = 8 using the Stroke direction concept[10].

3.7 Spatial Width or Spread of the Gaussian Kernel (σ_x, σ_y)

Different values from the set {4, 0.5λ, 0.7λ} where λ is the wavelength, are experimented with for spatial width of Gaussian envelope as per literature review[4,7,8]. For simplicity, spatial width in x and y direction are taken as equal ($\boldsymbol{\sigma}_x = \boldsymbol{\sigma}_y$) throughout.

3.8 Feature Set and Feature Size

The resultant convolved output matrix is of image size 32 x 32. To capture the inherent features from same, the Mean and Standard Deviation is calculated for both and. Hence four features given by {G_{even_Mean}, $G_{even\_Standard\_Deviation}$, G_{Odd_Mean}, $G_{odd\_Standard\_Deviation}$} are obtained corresponding to each of the filter convolved with the image as in[5]. Thus for each numeral image, $Gabor\_feature\_size = n_f{}^* \, n_\theta{}^* \, 4 = 5^* \, 8^* \, 4 = 160$ where n_f = *number of frequencies and* n_θ = *number of orientations*.

4. Results and Discussion

The three sizes of Gabor filter are experimented with and the best recognition result varying spatial width for each filter size is shown in Table 2. The SVM classifier with RBF kernel has better results overall and 31 x 31 filter size has given the maximum recognition accuracy 98.06%. Our results are comparable with the earlier reported results on ISI Devnagari Numeral database by Pal et al. using dimensional features (99.65%)[14], Bhattacharya et al. using wavelet based technique and chain code histogram (99.27%)[13], Singh et al. using recursive subdivision of numeral image (98.49%)[15], Aggarwal et al. using Gradient feature with Sobel operator (99.6%)[16]. No literature is found on ISI Data using the Gabor filter.

Comparing the result with peer research group utilizing Gabor feature for character recognition with different Standard Benchmark databases, our result 98.06% on ISI Standard Benchmark Devnagari Numeral database with the given data-size (Training Data: 19798, Testing Data: 3763) are satisfactory. Reported results in literature for the same are as follows- On ETL-1 Database of Handwritten Numerals with 10 classes and 1400 numerals per class (error rate 2.51%)[8], ETL-8 Database of Hand-printed Chinese characters with 55 classes selected and 160 patterns per class (error rate 2.4%)[7], MNIST Database of Handwritten numerals (Training set: 60,000, Testing set: 10,000) (classifier used: Polynomial, accuracy 99.47%)[9], (classifier used: MQDF, accuracy 99.13%)[10], CENPARMI Database(Training Set: 4000, Testing Set: 2000) (accuracy 98.95%)[9].

Table 2. Recognition accuracy achieved for feature gabor filter

Filter Size	1-NN	SVM		
		Linear	RBF	Polynomial
31x31	83.49%	94.31%	98.06%	97.87%
19x19	81.69%	91.89%	96.73%	96.38%
7x7	73.82%	77.25%	88.91%	89.55%

5. Conclusion

In this paper, the experiment has been carried out using the famous feature extraction technique of Gabor filter with the Nearest Neighbor and SVM classifiers for the recognition of handwritten Devnagari numerals. It is observed that the filter size 31 x 31 is indeed the best choice and cannot be compromised with lower sizes for reducing the computational heaviness of Gabor filter. The frequency and the orientation values for Gabor filter computation are carefully selected as per the shape characteristics and probable stroke widths of the handwritten numerals. Different spatial width values are experimented with to optimize the recognition accuracy. The results are comparable with the peer research group as Standard Benchmark database has been used. The recognition accuracy of 98.06% on ISI data using Gabor filter is comparable to the results available in literature utilizing other feature extraction techniques on same database and with the research group using Gabor filter feature extraction technique on different Standard Benchmark datasets.

6. Acknowledgement

We are thankful to CVPR unit, ISI, Kolkata for providing us the Standard Benchmark Handwritten Devnagari Numeral Database free of cost for research purpose and saving our time and effort to develop the same.

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