International Journal of Information Technology and Knowledge Management
January June 2009, Volume 2, No. 1, pp. 203-207

EVALUATION OF ORTHOGONAL DIRECTIONAL GRADIENTS ON HAND-PRINTED DATASETS

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In digital image processing and computer vision applications, the boundary / contour extraction and encoding are the important processes used for recognition and interpretation of images. The chain code based features are difficult to extract in noisy situation whereas there is no problem in extracting gradient based features. Several methods are used to compute the gradient direction of pixels used to represent an image. Some methods among these are Robert gradient, Prewitt gradient, Sobel gradient, Frei-Chen gradient, Kirsch gradient and Robinson gradient. In this paper, first four methods are compared in respect of their recognition performance on hand-printed character databases in noisy and noise-less situation. The performance comparison has been made on two different hand-printed datasets collected from different persons. One dataset belongs to Devanagari script consisting of 43 classes only. The second dataset belongs to Roman and consists of 10 classes.

***Keywords**:* Directional gradients, Hand-printed recognition, Devanagari script, Random noise, k-NN, MLP, Orthogonal gradients, First-derivatives.

1. Introduction

The boundary based feature extraction methods have been used in various image analysis and recognition applications. In visual scenes too, the boundary of an object plays an important role in identifying or recognizing it. In a given scene, if one object is overlapped over other and the boundary of upper object is not clear then it becomes very difficult to recognize the given object(s). Several methods have been used for detecting the boundaries of various objects present in an image. Boundary encoding means assigning a code to the pixels present on the image boundary or near boundary. The codes are generally assigned depending upon the location of a pixel on the image boundary. Two important methods used for boundary extraction and encoding are chain code and gradient based representation of images. In chain code representation, the image boundary is tracked and a boundary pixel of the given image is assigned a code depending upon its position from its previous boundary pixel. The chain codes are generally obtained using well-known Freeman chain code algorithm. The chain codes are difficult to extract in noisy situation. One more important method for encoding the boundary pixels uses the gradient of pixels present in an image. The importance of gradient direction was studied by Birk et al [4] for object recognition. Some methods used for computing the gradient magnitude and direction are: Robert gradient[1], Frei-Chen gradient[2], Prewitt gradient[3], Sobel gradient[17], Kirsch gradient[18] and Robinson gradient[10]. These methods are based on first-derivatives.

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Literature shows many features that have been used for the recognition of hand-printed character images pertaining to various scripts. Among these methods, the gradient based feature representation method is most promising. Srikantan *et al.* [7] encouraged its use first time in OCRs where they applied it for hand-printed character recognition using Sobel operator. Some hand-printed applications [5-9, 11-14] where gradient have been used and there are many more and it is also used for other pattern recognition applications.

In this paper, the recognition performance of four operators, used for computing the gradient of digital images, is compared in noisy and noise-less situation on hand-printed datasets. These four operators are: Robert gradient, Prewitt gradient, Sobel gradient and Frei-Chen gradient. Though, these operators are quite old but their relative comparison in respect of their recognition behavior in noisy and noise-less situations is quite important. Our Devanagari dataset consists of about 43 basic classes. The second dataset belongs to Roman and is consisting 10 classes only. The gradient features have been used for recognition by various authors but the performance comparison of different gradient operators on hand-printed datasets is not available in literature. Without performing experiments it is not possible to say that which gradient operator is better for which script. Two classifiers i.e. Multilayer Perceptron (MLP) and *k* Nearest Neighbour (*k*-NN) have been used for conducting experiments.

2. Contour Representation

The boundary of an object plays an important role in its identification or recognition. The abrupt change in pixel intensity in an image causes discontinuities that characterize the boundary of object in scene. Two classes of differential boundary detector are: first-order and second-order derivatives. In first-order the intensity change at a pixel in an image is measured by computing the change in gradient value at that pixel. This is also called as gradient based edge detection method. In this method edges are obtained by computing maximum and minimum in the first derivative of the image. For a given image pixel if its first derivative is maximum then its second derivative will be zero.

2.1 Gradient Estimation

The gradient of an image is a measure of the magnitude and direction of greatest change in image intensity *I(x, y)* at each pixel *(x, y)*. The gradient of an image *I(x, y)* at a pixel *(x, y)* is given by vector

$$\nabla I = \begin{bmatrix} G_x \\ G_y \end{bmatrix} \tag{1}$$

The components G_x and G_y of gradient may be calculated using following approximation

$$G_x(x,y) = \frac{\partial I(x,y)}{\partial x}, \quad G_y(x,y) = \frac{\partial I(x,y)}{\partial y} \tag{2}$$

The gradient direction at any pixel (*x, y*) gives the direction of greatest change in image intensity and is given as:

$$\Theta(x,y) = \tan^{-1}\frac{G_y(x,y)}{G_x(x,y)} \tag{3}$$

The angle is measured with *x*-axis (horizontal axis). The direction of the edge at a pixel (*x, y*) is perpendicular to the gradient vector at that point.

2.2 First Order Orthogonal Gradient Operators

Various operators such as Robert operator, Prewitt operator, Sobel operator, Frei-Chen operator, Krisch operator and Robinson operator can be used to compute the gradient of an image at a given pixel. These methods are based on first-derivatives. Among these first four methods generate gradients in two orthogonal directions in an image and last two use a set of directional derivatives to compute gradient direction. The different operators used in orthogonal gradients are given in Table 1.

The value of 'λ' in 3×3 window is 1, 2 and $\sqrt{2}$ for Prewitt, Sobel and Frei-Chen operators respectively.

Table 1
First-derivative Orthogonal Gradients and their Corresponding Operators

Operator Type	*Horizontal axis*	*Vertical axis*
Robert	$\begin{bmatrix} -1 & 0 \\ 0 & \boxed{1} \end{bmatrix}$	$\begin{bmatrix} 0 & -1 \\ 1 & \boxed{0} \end{bmatrix}$
Prewitt/Sobel/ Frei-Chen	$\begin{bmatrix} -1 & 0 & +1 \\ -\lambda & \boxed{0} & +\lambda \\ -1 & 0 & +1 \end{bmatrix}$	$\begin{bmatrix} -1 & -\lambda & -1 \\ 0 & \boxed{0} & 0 \\ +1 & +\lambda & +1 \end{bmatrix}$

Robert's operator is 2 × 2 and approximates the gradient at the centre of 4-neighbourhood and not at centre. They are efficient to use and more locally applied.

The Prewitt, Sobel and Frei-Chen operators are 3×3. Being odd in size, obviously they have a center. It is advantageous to use odd operators as compared to even as in case of later the value of gradient components approximated is inclined towards center pixel. It also helps in reducing noise effect by taking the average of neighborhood pixels. The Sobel masks have better noise suppression characteristics as compared to Prewitt due to the presence of weight 2 at middle locations in non-zero rows and columns. However, Frei-Chen used weight $\sqrt{2}$ at middle locations instead 1 or 2 in non-zero rows and columns so that the gradient is same along horizontal, vertical and diagonal edges. The Prewitt operator is more sensitive to horizontal and vertical edges than diagonal whereas Sobel operator is more sensitive to diagonal edges than horizontal and vertical [15].

2.3 Feature Extraction using Gradient Operators

Though, the components G_x and G_y are used to compute the gradient magnitude and gradient direction but the later contains more information as compared to former. So, the gradient direction is more important as far as feature representation of images is concerned for recognition. The gradient direction of an image at all the pixels is computed and stored in an array which has same size as that of an original image. This is also called as gradient map (GM). The GMs of a binary character image computed using various gradient operators is given in Figure 1.

Figure 1: (a) Binary Image 34×34 Pixels Size. Its GM Computed using (b) Frei-Chen Operator, (c) Prewitt Operator, (d) Sobel Operator and (e) Robert Operator

3. Classification Methods

We have conducted various experiments in this paper on Devanagari handwritten characters and Roman numerals using two classifiers i.e. multilayer perceptron (MLP) and k nearest neighbour (k-NN).

3.1 *k*-Nearest Neighbors Classifier

k nearest neighbor classifier is one among the instance-based methods and it is also called as lazy algorithm. In k-nearest neighbors (k-NN), the posteriori probability of occurrence of unknown pattern is predicted on the basis of frequency of its nearest k-neighbors in a given training sample set. Computation time to test a pattern in k-NN depends upon the number of training samples and the size of feature vector. As far as the space requirement is concerned, the classifier requires complete training dataset in memory. The performance of a classifier further depends upon the value of k, the size of training dataset, the metric distance used to measure the distance between a test sample and the training samples and the mode of decision (majority rule, weighted decision etc.).

3.2 Multilayer Perceptron

Multilayer feed forward neural network with error back-propagation is widely used classifier for hand-printed problems and it performs better as compared to many other classifies. In error back-propagation algorithm, the gradient-descent method is generally used to minimize the squared error cost function. The resilient propagation algorithm has been contributed by Riedmiller *et al*[19] to overcome the shortcomings of gradient descent method in which the size of change in weights, say Δw_{jk}, depends upon the learning rate η as well as on partial derivatives $\frac{\partial E}{\partial w_{jk}}$ of the error surface.

4. Experimental Results

For comparison purpose, the two datasets have been used. In case of Devanagari hand-printed character dataset, the experiments are conducted with 400 samples per class. In case of Roman hand-printed numeral dataset, the experiments have been conducted on 200 samples per class. The samples of each dataset are divided into two groups i.e. A and B. In case of Devanagari hand-printed dataset first 300 samples per class has been used for training and remaining 100 samples per class has been used for testing purpose. In case of Roman hand-printed numerals dataset first 150 samples per class has been used for training and remaining 50 samples per class has been used for testing purpose. The normalized images having size 45×45 pixels are taken for study purpose. In case of MLP, apart from input layer two more layers have been used. The size of input layer is same as the size of input vector which is 100 in all experiments. The size of middle layer varies from 40 to 70 and 90 to 120 for Roman numeral and Devanagari character respectively. If we increase the number of nodes beyond this range, then the recognition rate is not increased much and if we decrease the number of nodes beyond this range, then the error rate is increasing. The size of output layer is 10 and 43 for Roman numerals and Devanagari characters datasets. The MLP is trained using resilient propagation [19] as it is not much sensitive to parameter setting. We only need to optimize the size of middle layer as per our application.

4.1 Noise-Free Images

The experimental results on noise free character/numeral images using MLP classifiers are given in Table 2. The recognition result reported in each cell is average of about 6 trials for a specific value of number of nodes in middle layer in case of Table 2. Here NNML is number of nodes in mid layer. In case of k-NN, the experiments are conducted at different values of k. Only odd values have been used. The experimental results with k-NN at different values of k are reported in Table 3. The analysis of results listed in Tables (2-3) is given in Figure 2.

Table 2
Recognition Results of Four Gradient Operators with MLP at Different Number of Nodes in Mid-layer on Devanagari and Roman Numeral Hand-Printed Images

	Devanagari Character				*Roman Numeral*			
Gradient /NNML→ ↓	*90*	*100*	*110*	*120*	*40*	*50*	*60*	*70*
Prewitt	81.6	81.6	81.6	**81.8**	94.8	94.6	**95.5**	94.9
Sobel	80.7	81.1	**81.5**	81.2	94.2	94.5	94.5	**95.2**
Frei-Chen	81.4	**81.5**	81.4	81.3	94.5	**95.2**	94.5	93.4
Robert	80.3	80.2	80.2	**80.5**	93.7	**95.2**	94.6	94.5

Let us take the case of noise-less images. The error rate of Prewitt operator is small as compared to other operators using MLP classifier and this is true for both the datasets.

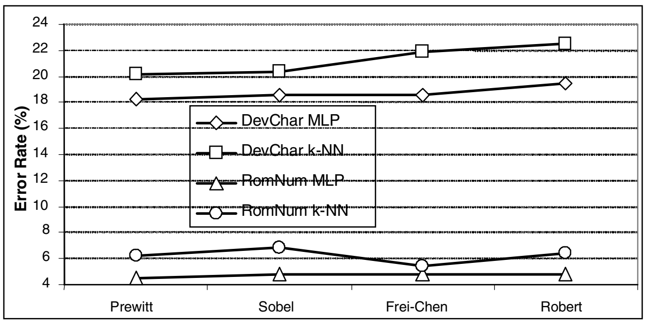

Figure 2: Error Rate with Different Gradient Operators with MLP and k-NN Classifiers on Devanagari and Roman Datasets

However on Devanagari the error rate of Robert operator using MLP is high. Though, it is not high on Roman numerals but comparable to Sobel and Frei-Chen. The discrimination ability of Prewitt operator is high as compared to other operators and it is low with Robert operator on noise-less images. The discrimination ability of Sobel and Frei-Chen operators is comparable on both datasets with MLP classifier whereas it is inconclusive in case of *k*-NN classifier.

Table 3
Recognition Results of Four Gradient Operators with *k*-NN at Different Values of *k* on Devanagari and Roman Numeral Hand-printed Images

	Devanagari Character					*Roman Numeral*				
Gradient/k→ ↓	*3*	*5*	*7*	*9*	*11*	*3*	*5*	*7*	*9*	*11*
Prewitt	79.0	**79.8**	79.7	79.2	79.3	**93.8**	93.8	93.8	93.2	93.2
Sobel	78.7	79.3	79.4	**79.6**	79.2	92.4	93.0	**93.2**	92.6	92.6
Frei-Chen	77.8	77.8	78.0	78.0	**78.1**	93.2	93.8	**94.6**	94.4	94.6
Robert	76.3	77.3	**77.5**	77.5	77.1	91.8	92.4	93.4	**93.6**	93.2

4.2 Noisy Images

The experiments are also conducted to know the discrimination ability of various methods under study on handwritten images in noisy situation. Initially the images are normalized to their standard size i.e. 45×45 and after normalization the noise is added to the images. A random white noise which is about 15% to the normalized image size is added to the images. The features have been extracted using all the four methods from the images once created by adding random white noise. The experimental results on noisy character/numeral images using MLP classifiers are given in Table 4. The experimental results with *k*-NN at different values of *k* are reported in Table 5. The scheme of recording the results is same as mentioned for Tables 2 & 3. The analysis of results presented in Tables (4 & 5) is given in Figure 3.

Table 4
Recognition Results of Four Gradient Operators with MLP at Different Values of Number of Nodes in Middle Layer on Devanagari and Roman Numeral Noisy Hand-printed Images

	Devanagari Character				*Roman Numeral*			
Gradient /NNML→ ↓	*90*	*100*	*110*	*120*	*40*	*50*	*60*	*70*
Prewitt	77.9	78.2	**78.3**	78.0	93.5	**93.9**	93.8	93.7
Sobel	76.7	**78.4**	**78.4**	77.4	92.6	94.0	92.4	**94.1**
Frei-Chen	77.5	**78.5**	77.5	78.0	94.2	**94.4**	94.1	94.1
Robert	74.1	**74.5**	74.1	74.3	91.3	**91.9**	91.7	91.8

Table 5
Recognition Results of Four Gradient Operators with *k*-NN at Different Values of *k* on Devanagari and Roman Numeral Noisy Hand-printed Images

	Devanagari Character					*Roman Numeral*				
Gradient/k→ ↓	*3*	*5*	*7*	*9*	*11*	*3*	*5*	*7*	*9*	*11*
Prewitt	76.4	77.8	78.0	77.9	**78.4**	**93.0**	92.4	92.0	91.8	92.2
Sobel	**78.5**	78.5	78.2	78.0	77.9	92.2	**93.2**	93.2	93.0	93.2
Frei-Chen	77.1	**77.7**	77.7	77.7	77.6	**93.6**	93.2	93.0	93.4	93.4
Robert	**73.5**	72.8	72.9	73.2	73.5	91.4	90.8	**91.8**	90.4	90.6

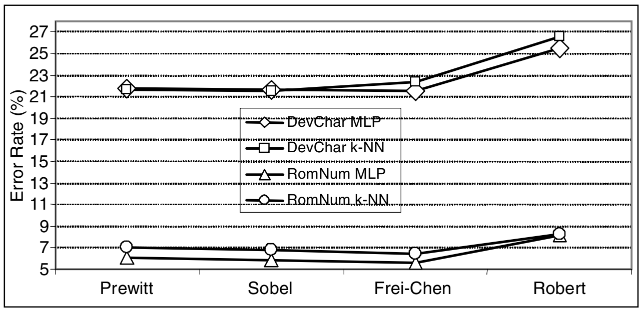

Figure 3: Error Rate with Different Gradient Operators using MLP and *k*-NN Classifiers on Devanagari and Roman Datasets in Presence Random of Noise

In case of noisy images, the error rate is high with Robert and comparable with other operators on both datasets using MLP. However for *k*-NN the error rate of Prewitt is low on Devanagari hand-printed and is small high as compared to Sobel and Frei-Chen on Roman numerals. If we look at majority of trials using MLP and *k*-NN classifiers we can say that the discrimination ability of Prewitt operator is comparable to Sobel and Frei-Chen and very large in comparison to Robert operator in noisy images.

From Figure 4, it is clear that the recognition performance of Prewitt and Robert operators affected a lot in noisy situation with *k*-NN where as the effect is almost equal for Sobel and Frei-Chen. The similar behavior is

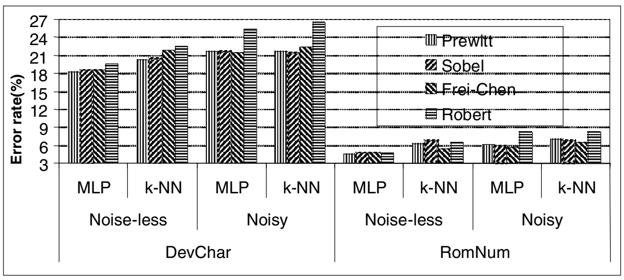

Figure 4: Effect on the Recognition Performance of Different Gradient Operators using *k*-NN and MLP Classifiers on Noisy and Noise-less Images Taken from Devanagari Character and Roman Numerals Datasets

observed with MLP classifier but the effect on drop in recognition rate is high in case of MLP classifier.

As far as it is concerned with the discrimination ability of MLP and *k*-NN classifiers, the former performs better as compared to later both in respect of time and accuracy. In noisy situation the performance of MLP and *k*-NN is almost same.

5. CONCLUSION

In overall, we can say that Prewitt operator performs better and Robert operator performs worst as compared to other operators studied here. The effect of noise on enhancing error rate is very high with Robert operator, small with Prewitt operator and little with Sobel and Frei-Chen operators. The effect of noise on enhancing error rate is high with MLP classifier as compared to *k*-NN. So in noisy situation it is better to use Sobel or Frei-Chen operator whereas in noise less images it is better to use Prewitt operator. The Robert operator is not good both in noisy and in noise-less situation. Among Sobel and Frei-Chen operator it is better to use Sobel operator as Frei-Chen requires floating point computation.

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