OFF-LINE TEXT-DEPENDANT WRITER RECOGNIZATION

Submitted by

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**PROJECT CERTIFICATE**

This is to certify that the Project entitled “OFF-LINE TEXT DEPENDENT WRITER RECOGNITION” submitted by **Shreya Das**, **Swagarika Jaharlal Giri**, RCC INSTITUTE OF INFORMATION TECHNOLOGY, Kolkata and **Mousumi Nand**i, INSTITUTE OF ENGINEERING AND MANAGEMENT, Kolkata to the Electronics and Communication Sciences Unit, Indian Statistical Institute, Kolkata towards the partial fulfilment of the participation in the Second Summer School on Computer Vision, Graphics and Image Processing during June 01 – July 15, 2016. The entire project work is carried out by them under my supervision. The contents of this Project have not been submitted to any other Institute or University for the award of any degree or diploma.

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**CONTENTS**

* Abstract
* Introduction
* System Extraction
* Feature Extraction
* Classification and recognization
* Experimental Result
* Database
* Conclusion

**ABSTRACT**

We have proposed a method for text dependent writer recognition system based on projection feature. Our feature includes horizontal, vertical and diagonal (in +45 and -45 degree) projections. After the feature extraction we have tested our algorithm on ISIHWR database using multiclass SVM classifier. Our experimental results showed good recognition accuracy.

**INTRODUCTION**

Writer recognition have gained increased importance recently, especially in the fields of forensic document examination and biometrics .The biometric modalities, including facial images, fingerprints, retina pattern, voice, signature and others have been investigated.

Automatic offline writer recognition is very important for forensic analysis, documents authorization, and calligraphic relic’s identification, etc. The offline text-independent writer recognition is to determine the writer of a text among a number of known writers using their handwriting images. Off-line handwriting recognition involves the automatic conversion of text in an image into letter codes which are usable within computer and text-processing applications. The data obtained by this form is regarded as a static representation of handwriting. Off-line handwriting recognition is comparatively difficult, as different people have different handwriting styles.

Application for writer recognition includes Biometric modalities. It is classified into two broad categories: physiological biometrics that perform person identification based on measuring a physical property of the human body (e.g. fingerprint, face, iris, retinal blood vessels, hand geometry, DNA) and behavioral biometrics that use individual traits of a person’s behavior for identification (e.g. voice, gait, keystroke dynamics, signature, handwriting). Writer identification therefore pertains to the category of behavioral biometrics.

Contrary to other forms of biometric person identification used in forensic labs, automatic writer identification often allows for determining identity in conjunction with the intentional aspects of a crime, such as in the case of threat or ransom letters. This is a fundamental difference from other biometric methods, where the relation between the evidence material and the details of an offense can be quite remote.

Word recognition is the ability of a reader to recognize written words correctly and virtually effortlessly. It is sometimes referred to as "isolated word recognition" because it involves a reader's ability to recognize words  individually from a list without needing similar words for contextual  help. Whereas writer recognition is to determine the writer of the text among a number of known writers using their handwriting images.

Text dependent approach identification of writers is based on specific targeted handwritten text where all the writers write the same text. While text independent approach identification of document’s writer is based on any written text. Dependent on the text content, text-dependent methods only matches the same characters and requires the writer to write the same text consequently. The text-independent methods are able to identify writers independent of the text content and it does not require comparison of same characters. Thus it is very similar to signature verification techniques and uses the comparison between individual characters or words . As Text dependent writing requires the same writing content this method is not apt for many practical situations.

There are two Writer identification methods-Online identification and Offline identification. In the former, the data are captured during the writing process by a special pen on an electronic surface. In the latter, the data are acquired by a scanner after the writing process is over. The off-line recognition is dedicated to bank check processing, mail sorting, reading of commercial forms, etc., while the on-line recognition is mainly dedicated to pen computing industry and security domains such as signature verification and author authentication. Different confidence measures are defined to assess the quality of the recognition. The performances of systems are evaluated compared on a large data set.

Feature selection methods are applied to improve the performance of an existing writer identification system. Various parameters influencing the performance of the system are systematically studied on a large data set.

In this project we have considered the problem of personal identification using samples of handwritten text. The objective is to identify the writer of the handwritten text. We have considered handwritten text for our analysis.

In the sections that follow, we have our feature on binary images. The black pixels in the binary image represent the handwriting ( foreground pixels)while the white pixels are used to denote the background.

**SYSTEM OVERVIEW**

Following Writer identification system consist of the pre-processing, feature extraction, classification and recognization. The schematic diagram is given this figure.

* Pre-processing a common name for operation with image at the lowest level of abstraction both Input and Output are intensity image. The aim of pre-processing is an improvement of image data that suppresses unwanted distortion or enhances some image feature important for further processing.
* Feature extraction is the method of building derived values ([features](https://en.wikipedia.org/wiki/Feature_(machine_learning))) intended to be informative and non-redundant, facilitating the subsequent learning and generalization steps, and in some cases leading to better human interpretations. Feature extraction is related to [dimensionality reduction](https://en.wikipedia.org/wiki/Dimensionality_reduction).
* Classification and Recognization is the process by which the feature extracted is then used to distinguish between number of sample and categorize them on the basis of feature vector. Recognization is process where the category so detected is matched with known set so that we could recognize which class particular set belongs.

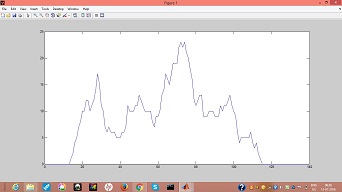
**FEATURE EXTRACTION**

Pre-processing: The salt-and-pepper noise is removed by single morphological opening and closing with structuring element of size just less than any acceptable blobs and resized the image in particular size as per requirement of feature. The resized gray image is converted into binary image. The process of Pre-Processing is shown in the figure.

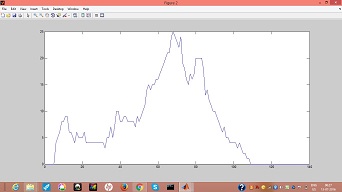
Feature Extraction is the most important part of Writer Identification/Recognition process as we have to determine the writer of the text or scanned image hence which feature to consider is very important [25] . By proper feature extraction we are able to classify them and recognize the style of writing of the writer. Effective feature extraction improves the recognition and decreases misclassification as stated by[6].In the following proposed method we have tried to extract the style of writing of the writer considering the following feature.

Diagonal Extraction Feature

Considering the resized image in 70X70 there are 139 diagonal lines and it checks if pixel is black and calculates the black pixel count along the diagonal.This is considering diagonal along 45 degree same method is repeated along -45 degree so that the total size of the diagonal feature is 139x2. Slant represents a very stable characteristic of individual handwriting and gives distinctive visual appearance to the text hence diagonal feature is being used to take into consideration the Slant of the text or direction information.

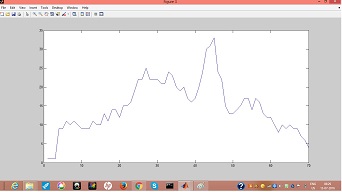
 

(45 degree projection) Feature of diagonal projection( 45 degree)

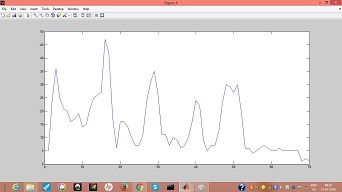
 

(-45 degree projection) Feature of diagonal projection( -45 degree)

Another important feature taken into consideration is height and width of the one writer’s writing varies from height and width of other writers writing. So in order to consider the height and width information horizontal and vertical pixel count is also taken as feature.

Horizontal projection Feature of Horizontal projection

Vertical Projection Feature of Vertical projection

**CLASSIFICATION AND RECOGNIZATION**

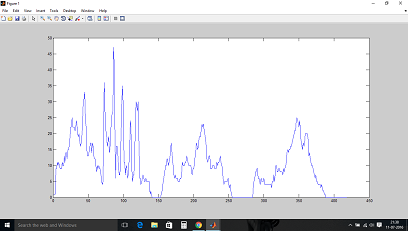
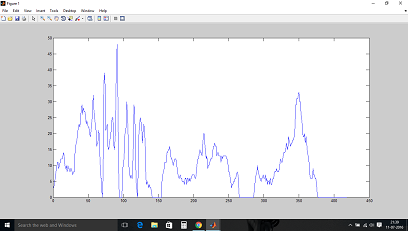
Classification stage is the most important part of the recognization system. In this proposed method classification is the most important part. We have used Support Vector Machine (SVM) classifier. The standard SVM classifier takes the set of input data and predicts the classifying class. SVM is trained over given data set and tested over data set and result is predicted. A Support Vector Machine (SVM) is a discriminative classifier formally defined by a separating hyper-plane. In other words, given labelled training data , the algorithm outputs an optimal hyper-plane which categorizes the new examples .A line is bad if it passes too close to the points because it will be noise sensitive and it will not generalize correctly. Therefore, our goal should be to find the line passing as far as possible from all points .Thus, the operation of the SVM algorithm is based on finding the hyper-plane that gives the largest minimum distance to the training examples. Twice, this distance receives the important name of margin within SVM’s theory. Therefore, the optimal separating hyper-plane maximizes the margin of the training data. . If all patterns in a dataset can be separated by a straight line or a hyper-plane, the dataset is said to be linearly separable .However, there are many problems, such as XOR, which are not linearly separable. SVM uses linear models to implement nonlinear class boundaries. It transforms the input space using a nonlinear mapping into a new space (F feature space). Then a linear model constructed in the new space can represent a nonlinear decision boundary in the original space: Suppose a two-class dataset is linearly separable. The maximum margin hyper-plane is the one that gives the greatest separation between the classes. Among all hyper-planes that separate the classes, the maximum margin hyper-plane is the one that is as far away as possible from the two convex hulls, each of which is formed by connecting the instances of a class. The instances that are closest to the maximum hyper-plane are called support vectors. There is atleast one support vector for each class, and often there are more. A set of support vectors can uniquely defines the maximum margin hyper-plane for the learning problem. All other training instances are irrelevant; they can be removed without changing the position and orientation of the hyper-plane.

Advantage of SVM includes 1. Produce very accurate classifiers. 2. Less over-fitting, robust to noise.  
Application of1.SVM are helpful in text and hypertext categorization , Classification of images can also be performed using SVMs. Experimental results show that SVMs achieve significantly higher search accuracy than traditional query refinement schemes.

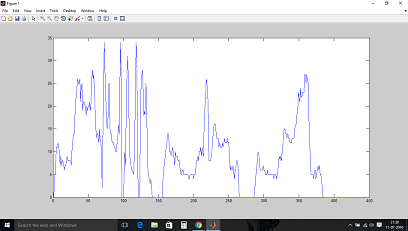
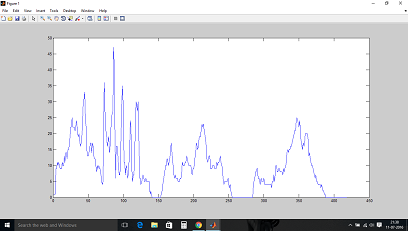
There is the plotted feature vector of diagonal feature combined with horizontal and vertical pixel count resizing the image into fixed size of 70X70. Initial 70 corresponds horizontal projection followed by vertical projection followed Diagonal projection 45 degree and -45 degree.

The plotted feature vector clearly explains that there is great similarity between the feature vector of the text depended writing of same writer. This similarity between the feature vector of text of same writer lead to proper classification

Fig15 Fig 16

Now consider figure they are the plotted feature vector of 2 different writer and there is great difference in the plotted feature vector. The difference can easily be identified. This difference in the feature vector is used to identify the difference between the 2 different writer. By training the pattern generated by for text depended feature vector the classifier is trained and by testing the feature vector of handwritten image of unknown writer and try to match it with feature vector of already trained feature vector of writer and try to identify the actual writer.



Commonly used kernels in our case are Linear kernel, polynomial kernel, Gaussian Radical Basis Function (RBF) and sigmoid. We have considered Linear and polynomial kernel and verified which kernel shows better efficiency for a given data.

We have considered our 5 sets set1 ,set2, set3, set4 set5 and each set has 33 words that are part of legal bank cheque valid set and each word has 90 instance corresponding to different writer thus we have 5 instance of each word for a single writer in this way we have 33 words hence 5x33 sample of writing of a single writer and such 90 writer are there.

On basis of our feature we have obtained feature vector and considering single word e.g ‘one’ of 90 writer in each of 5 set. For each set we get feature vector of size 90 x length of feature vector. This process is repeated for each set then we apply the SVM classifier taking into consideration all combinations of 4 set as train and 1 set as test. The predicted writer for all 90 instances provided as test is stored. The same process is repeated for all 33 words storing their individual predicted writer.

Thus the first row corresponds to the individual reading of word ‘one’ word ‘two words ‘three’ i.e. all 33 samples of valid words we considered and value predicted by the SVM classifier on the basis of the feature we used to train the classifier. The maximum frequency of the writer predicted for row one is considered as the actual predicted writer for the corresponding instance of the data set given. The same process is repeated for all 90 samples of words and corresponding writer is predicted for each row. The final predicted writer for each of 90 samples is compared with the actual writer of the sample and efficiency is calculated.

We consider all possible combination of test and train and repeat the same process to estimate the overall efficiency of the feature.

**EXPERIMENTAL RESULT**

**DATABASE**

To implement our algorithm we have developed a handwritten word database. First 61 words identified whose combination represent ant legal amount of written in words in Indian bank cheque and also in other relevant places. These words are:

One, Two, Three, Four, Five, Six, Seven, Eight, Nine, Ten, Eleven, Twelve, Thirteen, Fourteen, Fifteen, Sixteen, Seventeen, Eighteen, Nineteen, Twenty, Thirty, Forty, Fifty, Sixty, Seventy, Eighty, Ninety, Rupees, hundred, thousand, lakh, crore.

For database generation, the above words are written by several writers. Each writer is requested to write each words five time using black ink on white A4 sheet. Writers are allowed to write freely in their own style without any constraint such as maintaining strictly horizontal line or maintaining words or character gaps. These A4 are scanned and resolution 300 ppi in gray scale. Here all greylevel image are converted to binary image by Otsu’s method. Then line and word segment are done to extract the words from the scanned documents using the method described in[25]. In this experiment we have used handwrittien word sample of 90 writer so we have 90X30X5=13500 sample based on five sample of each word. The database contains 90X30 templates of different words. Figure 4 shows few templates of different words as example.

Fig 3 Fig 4

Fig 5 Fig6

The corresponding figure are sample of images of the data set. Figure 5 and 6 corresponds same word ‘One’ written by 2 different writer. Figure 3 and 4 corresponds to word ‘two’ of different writer. Whereas figure3 and figure 5 corresponds to different word of same writer

We have considered 90 writer for each word model and there are 33 word model. The scanned .bmp image are grey scale images they are converted into binary image and the resized to size 70x70 . There are 5 such set which include 33 word model and each model includes 90 writer. Each word model is subjected to projectional feature so as to extract the feature vector. On basis of value of feature vector feed into SVM classifier for each word model after training and testing these are the values of c, t and g for each word model.

Linear kernel, polynomial kernel, Gaussian Radical Basis Function (RBF) used in respective Word sample and corresponding C ,G values.

|  |  |  |  |
| --- | --- | --- | --- |
|  | C | t | g |
| 1 | 1 | 0 | - |
| 2 | 100 | 1 | 0.001 |
| 3 | 0.1 | 0 | - |
| 4 | 0.9 | 0 | - |
| 5 | 100 | 0 | - |
| 6 | 10 | 0 | - |
| 7 | 1 | 0 | - |
| 8 | 100 | 0 | - |
| 9 | 100 | 0 | - |
| 10 | 100 | 0 | - |
| 11 | 130 | 0 | - |
| 12 | 0.1 | 0 | - |
| 13 | 0.9 | 0 | - |
| 14 | 10 | 1 | 0.1 |
| 15 | 120 | 1 | 0.1 |
| 16 | 100 | 0 | - |
| 17 | 100 | 0 | - |
| 18 | 10 | 0 | - |
| 19 | 10 | 0 | - |
| 20 | 10 | 0 | - |
| 21 | 0.1 | 0 | - |
| 22 | 130 | 0 | - |
| 23 | 130 | 0 | - |
| 24 | 10 | 0 | - |
| 25 | 50 | 0 | - |
| 26 | 160 | 0 | - |
| 27 | 80 | 0 | - |
| 28 | 160 | 0 | - |
| 29 | 1 | 0 | - |
| 30 | 10 | 0 | - |
| 31 | 110 | 0 | - |
| 32 | 10 | 0 | - |
| 33 | 70 | 0 | - |

This the value of c, g, t of respective word sample as they show maximum efficiency in these respective values. The above table clearly shows that linear kernel of SVM classifier shows maximum efficiency for most of the cases. The words of the data set ‘two’, ‘fourteen’ and ‘fifteen’ shows maximum efficiency in Polynomial kernel.

Different combination of test and train are considered and the following values are observed.

|  |  |  |  |
| --- | --- | --- | --- |
| TRAIN SET | TEST SET | WORD | AVERAGE EFFICIENCY |
| ONE SET | FOUR SET | 1 | 15.70 |
|  |  | 2 | 23.44 |
|  |  | 3 | 25.11 |
|  |  | 4 | 27.33 |
|  |  | 5 | 28.44 |
|  |  | 6 | 40.83 |
|  |  | 7 | 25.89 |
|  |  | 8 | 27.72 |
|  |  | 9 | 25.55 |
|  |  | 10 | 23.27 |
|  |  | 11 | 17.56 |
|  |  | 12 | 20.56 |
|  |  | 13 | 22.67 |
|  |  | 14 | 25.67 |
|  |  | 15 | 27.67 |
|  |  | 16 | 25.00 |
|  |  | 17 | 24.50 |
|  |  | 18 | 23.15 |
|  |  | 19 | 23.72 |
|  |  | 20 | 24.33 |
|  |  | 21 | 31.17 |
|  |  | 22 | 32.33 |
|  |  | 23 | 33.17 |
|  |  | 24 | 28.61 |
|  |  | 25 | 29.78 |
|  |  | 26 | 27.67 |
|  |  | 27 | 22.28 |
|  |  | 28 | 26.44 |
|  |  | 29 | 23.78 |
|  |  | 30 | 23.00 |
|  |  | 31 | 24.44 |
|  |  | 32 | 24.44 |
|  |  | 33 | 16.21 |

|  |  |  |  |
| --- | --- | --- | --- |
| TRAIN SET | TEST SET | WORD | AVERAGE EFFICIENCY |
| TWO SET | THREE SET | 1 | 32.84 |
|  |  | 2 | 30.37 |
|  |  | 3 | 34.96 |
|  |  | 4 | 38.34 |
|  |  | 5 | 40.67 |
|  |  | 6 | 40.26 |
|  |  | 7 | 43.30 |
|  |  | 8 | 38.45 |
|  |  | 9 | 39.37 |
|  |  | 10 | 37.96 |
|  |  | 11 | 35.37 |
|  |  | 12 | 26.52 |
|  |  | 13 | 32.74 |
|  |  | 14 | 34.33 |
|  |  | 15 | 39.23 |
|  |  | 16 | 35.89 |
|  |  | 17 | 37.17 |
|  |  | 18 | 33.63 |
|  |  | 19 | 35.63 |
|  |  | 20 | 39.51 |
|  |  | 21 | 39.51 |
|  |  | 22 | 43.26 |
|  |  | 23 | 50.30 |
|  |  | 24 | 45.56 |
|  |  | 25 | 42.48 |
|  |  | 26 | 42.41 |
|  |  | 27 | 41.96 |
|  |  | 28 | 34.74 |
|  |  | 29 | 38.32 |
|  |  | 30 | 35.28 |
|  |  | 31 | 34.89 |
|  |  | 32 | 35.59 |
|  |  | 33 | 21.11 |

|  |  |  |  |
| --- | --- | --- | --- |
| TRAIN SET | TEST SET | WORD | AVERAGE EFFICIENCY |
| THREE SET | TWO SET | 1 | 37.11 |
|  |  | 2 | 35.06 |
|  |  | 3 | 40.39 |
|  |  | 4 | 40.26 |
|  |  | 5 | 44.17 |
|  |  | 6 | 45.33 |
|  |  | 7 | 48.34 |
|  |  | 8 | 45.00 |
|  |  | 9 | 42.00 |
|  |  | 10 | 43.06 |
|  |  | 11 | 40.72 |
|  |  | 12 | 32.05 |
|  |  | 13 | 37.66 |
|  |  | 14 | 40.56 |
|  |  | 15 | 45.11 |
|  |  | 16 | 48.46 |
|  |  | 17 | 42.94 |
|  |  | 18 | 39.00 |
|  |  | 19 | 41.12 |
|  |  | 20 | 46.44 |
|  |  | 21 | 48.50 |
|  |  | 22 | 52.22 |
|  |  | 23 | 49.92 |
|  |  | 24 | 46.89 |
|  |  | 25 | 45.39 |
|  |  | 26 | 46.00 |
|  |  | 27 | 39.78 |
|  |  | 28 | 39.78 |
|  |  | 29 | 43.06 |
|  |  | 30 | 38.14 |
|  |  | 31 | 38.63 |
|  |  | 32 | 38.22 |
|  |  | 33 | 23.63 |

|  |  |  |  |
| --- | --- | --- | --- |
| TRAIN SET | TEST SET | WORD | AVERAGE EFFICIENCY |
| FOUR SET | ONE SET | 1 | 36.07 |
|  |  | 2 | 38.22 |
|  |  | 3 | 43.56 |
|  |  | 4 | 48.22 |
|  |  | 5 | 50.00 |
|  |  | 6 | 51.31 |
|  |  | 7 | 52.89 |
|  |  | 8 | 47.78 |
|  |  | 9 | 47.33 |
|  |  | 10 | 47.33 |
|  |  | 11 | 47.33 |
|  |  | 12 | 42.89 |
|  |  | 13 | 34.22 |
|  |  | 14 | 42.89 |
|  |  | 15 | 45.45 |
|  |  | 16 | 47.78 |
|  |  | 17 | 54.00 |
|  |  | 18 | 45.11 |
|  |  | 19 | 39.78 |
|  |  | 20 | 46.22 |
|  |  | 21 | 50.89 |
|  |  | 22 | 53.78 |
|  |  | 23 | 59.78 |
|  |  | 24 | 55.11 |
|  |  | 25 | 50.64 |
|  |  | 26 | 50.22 |
|  |  | 27 | 50.89 |
|  |  | 28 | 46.22 |
|  |  | 29 | 46.44 |
|  |  | 30 | 43.33 |
|  |  | 31 | 45.11 |
|  |  | 32 | 42.89 |
|  |  | 33 | 36.00 |

As it was observed that the individual efficiency of the word after consideration of all possible values of test and train is not satisfactory hence we have combined 33 model to acquire quite better results. As the database we have used each writer has written 33 words. Hence by using feature vector of 33 word of a particular writer is used to determine the writer . That showed good result and efficiency of up to 94.66% after training with 4 set and testing with 1 set. 91.37% after training with 3 set and testing on 2 set, 90.37% after training with 2 set and testing with 3 test and 85.53% on training with 1 set and testing with 4 set.

**CONCLUSION**

The approach proposed by us is a method for offline Text dependent Writer Identification based on horizontal, vertical and diagonal in both direction. We calculated the total pixel count in all of the four cases. It is a statistical approach for Writer Identification. It helped us to estimate the overall distribution of the pixel. We have also considered the overall pixel count to understand the style of writing of the writer also with it we have considered horizontal continuous black pixel count to determine the style of writing. We used the word level feature of handwriting which is more suitable to describe the individuality of the writer than page level. We obtained maximum efficiency of 96.66. In future we would like to work on Text independent Writer identification.

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