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Different Classification Techniques for Character Recognition: A Survey

Mayuri Rastogi
Department of Computer Science
Moradabad Institute of Technology
Moradabad, UP, INDIA
Email: diligentmayuri@gmail.com

Sarita Chaudhary
Department of Computer Science
Moradabad Institute of Technology
Moradabad, UP, INDIA
Email: sarita27jun@gmail.com

Shiwani Agarwal
Department of Computer Science
Moradabad Institute of Technology
Moradabad, UP, INDIA
Email: shiwani.agarwal91@gmail.com

ABSTRACT

Character recognition (CR) has been widely studied in the previous half century and develops to a level sufficient to produce technology determined applications. Nowadays, the precise recognition of machine printed characters is considered mainly a solved trouble. A lot of commercial products are paying attention towards that way, achieving high recognition rates. At the recognition phase a features are extracted from Characters in order to classify them to predefined classes techniques. However, handwritten character recognition is reasonably difficult. So, handwritten recognition documents is still a subject of active research Now, the quickly growing -computational power enables the execution of the present CR methodologies and creates a rising demand on many promising application field, which require more highly developed methodologies. This material serves up as a direct and update for readers working in the CR area. First, the chronological evolution of CR systems is presented. Then, the available CR techniques with their superiorities and weaknesses are analysis. Finally, the present status of CR is discussed, and strategy for future research is suggested. Particular attention is given to the finest classification technique for off-line hand-writing recognition since this region requires extra research to reach the eventual goal of machine simulation of human analysis. It describes difficultés, recent achèvements in all aspects of handwriting recognition. Some experimental results are also included.

Index Terms: Character recognition (CR), Feature extraction, Off-line handwriting recognition, Segmentation, Training and Recognition.

1. INTRODUCTION

Character recognition (CR) is an outline of pattern recognition process & Image processing. In actuality, it is not simple to achieve 100% accuracy using any procedure. Even humans also will make incorrectness when come to pattern recognition. [1].A number of reasons which cause inaccuracy like Pattern twist, dwindling of paper, and reality of unwanted objects or confused patterns will have an effect on the percentage correctness & performance.

Some problem has been addressed by many researchers in offline handwritten document for a considerable amount of time. [2] [3] In spite of the fact isolated character recognition (CR) is on its way to being solved, making sensible recognition rates 1.5. Still researchers concentration for the better recognition of handwritten character. Earlier Research, have some limitations in procedure for the recognition Systems, which can be classified by two major ways: the data acquisition process i.e. offline or on-line and image processing

In Off-line character recognition, the hand written is converted into string of 0's & 1's bit pattern or also called digitization by an optically digitizing device such as camera or optical scanner. After next stage, recognition is done on this bit pattern figures of hand-written text.

In recent Years, the focal point of attention is reallocated towards the recognition of hand-written script as well.

Some applications of handwritten recognition Systems included: Bank cheque, postal address recognition and processing tax forms. The study carry out researches in the Direction of the Character recognition.

The primary lead of the off-line recognizers is to permit the formerly written and in print texts to be process and recognized.

There are 4 major stages in the Character Recognition system:

1. Pre-processing,
2. Segmentation,
3. feature Extraction
4. Training and recognition,

A. Image Acquisition

Here input image taken throughout camera or by scanner. The input taken possibly will be in gray, colour form.

B. Image Preprocessing

In preprocessing step, output of the image acquisition is supply as input to the next phase. In this footstep, firstly the output is converted into the binary form by turning over '1' to black and '0' to white piece of the scanned image. This may hold some unclear or noise. Noise may have an effect on the correctness of the classification presentation.

Noise removal or Filtering

It contain various techniques of cleaning, smoothing, sharpening of character etc are used to remove noise. Noise term means as any ruinness in the image due to outside disorder. Superiority of handwritten documents depends on different reason like causes disconnected line piece, strike and gaps in lines, overflowing loops etc. shrinking of paper and pen, aging of papers, color of ink and many more. Some noise is salt and pepper noise, Gaussian noise and using some filtering technique & dilation and erosion operation, can be removed noises to some extent. Technical details of filtering can be found in [4]. It is obligatory to get rid of these imperfections. No. of available noise reduction practice can be categorized in two major set as filtering, morphological operations.

It aspire to remove noise and diminish forged points, generally initiate by uneven writing surface and poor sampling rate of the data acquirement device. Various spatial and frequency domain filters can be designed for this use like Low pass filtering, or known as "smoothing", is in use to remove high spatial frequency noise from a digital image. The fundamental idea is to convolute a pre-defined mask with the image to assign a value to a pixel as a purpose of the gray values of its neighboring pixels. Filters can be measured for smoothing, sharpening, thresholding, get rid of colored background and distinction modification purposes [5].

Morphological Operations

The necessary idea at the back of the morphological operations is to fill the gaps and bridge of character. Morphological operations can be effectively used to remove the noise on the document images due to miniature quality of paper and ink, as well as unpredictable hand movement. Therefore various morphological operations can be designed to attach the broken strokes decompose the connected strokes; smooth the outline[5].

Skeletonization

It job is to carry out operation crisper image by reducing the binary-valued image area to lines that approximate the skeletons of the region. A wide-ranging examination of thinning methodologies is explained in [6].

Normalization

Its purpose is to change the random sized image into some standard sized image. This size normalization evade inter class disparity among characters as shown in fig 1. Few processes for size normalization are Bilinear, Bicubic interpolation techniques discuss in [7].

C. Segmentation

After completing pre-processing process, output of preprocess phase enter as an input in segmentation phase. This phase slice the document into its sub components. It contains various segmentation like word segmentation, line segmentation and character segmentation. approach for character segmentations [8] are based on i) projection analysis and ii) connected section labeling .

Segmentation is a significant stage, since the amount one can reach in separation of characters directly power the recognition rate of the characters.

Explicit Segmentation

The procedure of Cutting up the image into major components is given a fussy name, "dissection". Dissection is a process that examine an image without using correct category of shape information.[9] The computation for good segmentation is the conformity of general property of the segments with these predictable for valid characters. Moreover, explicit segmentation can be subjected to estimate using linguistic framework.

Implicit Segmentation

It investigates the image for components that match predefined classes. This segmentation move toward on recognition[10]. Segmentation is carrying out for recognition assurance, including syntactic or semantic exactness of the overall consequence.

D. Feature Extraction

This is also called as relevant feature extraction & provide feature from particular areas. Features are a set of numbers that confine the most important characteristics of the segmented image. There is dissimilar feature extraction methods proposed for character recognition additional feature extraction techniques explain in [11][12] [13].

E. Recognition Methods

The output of feature extraction is a feature vector obtained from previous phase is assigned as an input to next phase i.e. classification or class label and recognized by means of supervised and unsupervised method. Here the data set is separated into training and test set for every character. Character classifier can be Baye's classifier, Neural networks with or without back propagation, Radial basis function, Nearest neighbor classifier, Linear Discriminant functions and Support vector machine.

The Future Research Directions

We sum up the labeling methods in collection of statistical methods, artificial neural networks (ANNs), multiple classifier combination and kernel methods.

Statistical methods: Statistical classifiers are groundwork in the Bayes decision rule, and can be alienated into parametric ones and non-parametric ones [14]. Non-parametric process, such as k-NN rule, are not realistic for real-time appliance since all training example are stored and compared which affected Gaussian density with a range of restrictions, the Bayesian discriminant principle is reduced to a (LDF) linear discriminant function, (QDF) quadratic discriminant function [15] steady the performance of QDF through flatening the covariance matrices. The modifiedQDF (MQDF) engage less parameters and lower calculation than the QDF, and which results in better generalization correctness.

Artificial neural networks (ANN): Feedforward neural networks, together with multilayer perceptron (MLP), radial basis function (RBF) network, higher-order neural network (HONN), etc., have been widely applied to pattern detection. The connecting weights are usually adjusted to minimize the squared error on training example in supervised learning. for every class was shown to get better the classification accuracy Using a modular network [16]. A network with local connection and sharedweights, identify as convolutional NN, has descriped great success in character recognition . The RBF network can give way viable accuracy with the MLP when training all factor by error minimization [17]. The functional-link network is also called as, HONN or polynomial classifier (PC). By using dimensionality reduction before polynomial expansion, its complexity can be reduced or another term is selection .Supervised learning examples are learning vector quantization (LVQ) of Kohonen It is a method which give higher classification accuracy than VQ. A few development of LVQ learn prototypes not by heuristic adjustment but also by error minimization [17].

Kernel methods: Increasing concentration and have shown finer performance in pattern recognition in Kernel methods, are support vector machines (SVMs) [18] primarily and (KPCA) kernel principal component analysis, (KFDA) kernel Fisher discriminant analysis, etc., are receiving An support vector machines is a binary classifier by discriminant function being the weighted combination of kernel functions more than training example. After learning by quadratic programming (QP), the nameof support vectors (SVs). comes up when the samples of non-zero weights are consider .For multi-class classification, combined binary SVMs in either one against-one or some-against others scheme . SVM classifiers have been typically practical to small category set problems due to the high complexity of training and execution. A approach to alleviate the calculation cost is to employ a neural or statistical classifier for selecting two candidate classes, which are then distinguish by SVM [18].

Multiple classifier combination: Combining multiple classifiers has given more improving correctness than single classifiers [19]. Comparitive sequential (cascaded, vertical) combination, Parallel (horizontal) combination is more often adopted for high accuracy, whichis mainly used for accelerating large category set classification. The decision combination methods are group into rank-level, abstract level and measurement-level combination [20]. For character recognition, united classifiers stand on dissimilar method of pre-processing, feature extraction, and classifier models is capable.The deformations of training example can also be used to train the classifier for superior generalization presentation .

Table 1: An illustration of error rates (%) on the MNIST test sample.

Feature	pixel	PCA	grad-4	grad-8
k-NN	3.6	3.0	1.2	0.9
MLP	1.9	1.84	0.8	0.6
RBF	2.5	2.2	0.9	0.6
PC	1.6	N/A	0.8	0.5
SVC-poly	1.6	1.4	0.7	0.5

2. PERFORMANCE COMPARISON

The research of character recognition is different in much issue such as the pre-processing procedure, feature extraction representation, classifier structure and learning algorithm. Only a some works have compared distinct classification methods based on the similar feature data.

In the subsequent, we primary mention some high recognition accuracies account on well-known sample databases, and then sum up some classification consequences on ordinary feature data. Handwritten character recognition has been most extensively tested in pattern classification for its extensive applicability and the easiness of implementation. Some popular databases are NIST SD19, MNIST, etc. The database NIST SD19 contains huge number of character images, but researchers frequently use dissimilar division of figures for testing and training. Hence, we collect a number of results reported on MNIST databases, which are separation into standard training and test sets.

This set was measured difficult, but it is simple to attain a recognition rate over 98% by take out statistical features and training classifiers. Suen et al. account a exact rate 98.85% by training NN on 450, 00 trial [3]. Correct rates over 99% have been given by (PC) and SVMs with training 4, 000 samples, [4, 20].

The MNIST database hold 10, 00 test samples and 60, 00 training samples and selected from the NIST SD19. LeCun et al. gather a number of test accuracies well-known by a mixture of classifiers [2]. An elevated correctness, 99.30%, was certain by a boosted convolution neural network trained through fuzzy data. Simardet al. improved both the indistinct example generation and the execution of CNN and resulted in test precision 99.60%. Instead of the trainable feature extractors in CNN, take out heuristically selective features also guide to elevate accuracies.

2.1 Statistical *vs*. Discriminative Classifiers

Margin-based classifiers also refer as discriminative classifiers as those support on minimum error training, including

Neural networks and SVMs, for which the parameters of one class are trained on the example of all classes. For statistical classifiers the parameters of one class are expected from the example of its own class only[21] .We contrast the distinctiveness of two kinds of classifiers in the subsequent admiration.

2.2 Neural Networks *vs.* SVMs

Neural classifiers and SVMs demonstrate dissimilar property in the subsequent respects.

- **Complication of training:** Through gradient descent, parameter of neural classifiers is normally adjusted. By provide the training example a set number of flounces, the training time is linear with the number of samples. [22]In SVM, quadratic programming (QP), are trained and the training time is usually proportional to the square of amount of samples.
- **Elasticity of training:** The parameter of neural classifiers can be accustomed in layout level training by gradient descent with the aspire of optimizing the global presentation [2, 37]. In this case, the neural classifier is surrounded in the layout recognizer for character recognition. On the other hand, SVMs can only be trained at the stage of holistic outline.
- **Model selection:** The simplification performance of neural classifiers is responsive to the size of pattern, and the choice of an proper structure relies on cross-validation. The junctions of neural network training go through from local minima of error surface. On the other hand, the quadratic programming learning of SVMs assurance of finding the global optimum. The presentation of SVMs depends on the choice of kernel type and parameters.
- **Classification correctness:** SVMs have been verified higher classification accuracies to neural classifiers in much trial.
- **Storage and execution complication:** SVM learning by quadratic programming repeatedly consequences in a large number of SVs, which should be stored and calculate in classification. Neural classifiers have much less parameters, and the quantity of parameters is simple to manage. In a word, neural classifiers consume less storage and calculation than SVMs.

3. IMPROVEMENTS OF ACCURACY

Accuracies lesser than 90% are normally accounted to difficult cases like unhindered cursive script recognition. Superior accuracy is always preferred. It can be attaining via involved in each processing task: pre-processing, feature extraction, sample generation, etc. We here of only talk about some matter associated to classification and learning.

- **Feature conversion and selection:** Feature alteration methods, including PCA and FDA, have been demonstrated efficient in pattern categorization, but no technique declare to discover the best

  Feature subspace. Generalized conversion methods based on relaxed density assumption and those based on discriminative learning are expected to find enhanced feature spaces. On the other hand, we can take out a large amount of features, and automatic feature selection may guide to improved classification than artificial selection.
- **Sample production and selection:** Training with unclear samples has resulted in enhanced simplified performance, but superior methods of unclear sample generation are yet to be found. Sample selection from very large data set is important to assurance the effectiveness and worth of training.
- **Mutual feature selection and classifier design:** To select features and design classifier jointly may guide to recovered classification performance. The Bayesian network belongs to such type of classifiers and is at the present being studies intensively.

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