BACKGROUND STUDY

Bankers accept cheques and demand drafts from their customers for collection. They get them collected by presenting them to the other banks through clearing or by post or by courier.

When a customer wants to submit a cheque for collection to the banker, he can personally hand over the cheque to the officer who is handling the department and he will be affixing his signature along with the seal of the branch in the counterfoil of the remittance slip which plays a crucial role in case of any dispute in collecting the cheque. Alternatively, the cheque along with the remittance slip can be dropped in a separate cheque drop box kept at the counter inside the bank branch.

The employees will clear the cheques at the appropriate time and this saves the time of customers since they don't have to wait in queues to submit cheques. However, the customer takes a huge risk in depositing the cheques in the cheque drop box. Since he is not having any documentary proof for having submitted the cheque to the bank, he cannot question the banker for any loss of the cheque or presentation of the cheque in delayed manner. Consequently to fasten the clearing process more employee are required. In addition to this, generating statistical estimation of periodical transactions is a tedious and protractile process.

A smart cheque drop box will evaluate whether a cheque is a valid bank cheque or not. It will issue a receipt to each customer and will be able to give the bank statistical data about periodical transactions. To validate a cheque, it will scan the hand written bank account number and phone number to determine the digits followed by tallying them with existing user records. Detection and recognition of hand written digits will be done by a machine learning based framework.

Handwritten character recognition

Handwriting recognition has always been a challenging task in pattern recognition. Many systems and classification algorithms have been proposed in the past years. But since handwriting depends much on the writer and because we do not always write the same character in exactly the same way, building a general recognition system that would recognize any character with good reliability in every application is not possible. Moreover poor paper quality, distortion from binding, poor inking, seepage of ink, etc. makes it a difficult task to extract handwritten characters. Typically, the recognition systems are tailored to specific applications to achieve better performances. In particular, unconstrained handwritten digit recognition has been applied to recognize amounts written on checks for banks or zip codes on envelopes for postal services (the USPS database). In these two cases, good results were obtained. An unconstrained handwritten digit recognition system can be divided into several stages: pre-processing (filtering, segmentation, normalization, thinning, etcetera), feature extraction (and selection), classification and verification.

- **Pre-processing –** The aim of pre-processing is an improvement of the image data that suppresses unwanted distortions or enhances some image features important for further processing. For example: restoring distorted pixel by using value of neighbouring pixels, pixel brightness transformations, geometric transformations, grey scale transformations, brightness correction, etc.
- **Feature extraction –** Feature extraction is a pre-processing step that aims at reducing the dimension of the data while extracting relevant information. A good set of features should

represent characteristics that are particular for one class and be as invariant as possible to changes within this class. Commonly used features in character recognition are: zoning feature, structural feature, directional features, crossing points and contours. A feature set made to feed a classifier can be a mixture of such features. Besides, to reduce the size of the feature set, feature subset selection can be applied on the extracted features. . In handwriting recognition, features are created from knowledge of the data.

Related Literature Review

The performance of character recognition largely depends on the feature extraction approach and the classification/learning scheme. For feature extraction of character recognition, various approaches have been proposed [1]. Many experiments have shown that the stroke direction feature [2, 3], a statistical feature, is one of the most efficient features for handwritten character recognition [4]. The statistical features and local structural features are stored in a feature vector, which corresponds to a point in the feature space.

The task of classification is to partition the feature space into regions corresponding to source classes or assign class confidences to each location in the feature space. Statistical techniques, neural networks and Kernel based methods have been widely used for classification due to the implementation efficiency.

Statistical classifiers are rooted in the Bayes decision rule, and can be divided into parametric ones and nonparametric ones [7, 8]. Non-parametric methods, such as Parzen window, the nearest neighbour (1-NN) and KNN rules, the decision-tree, the subspace method, etc., are not much used, since all training samples are stored and compared. Parametric classifiers include the linear discriminant function (LDF), the quadratic discriminant function (QDF), the Gaussian mixture classifier, etc. In character recognition community, the modified quadratic discriminant function (MQDF2) proposed by Kimura et al. has been widely used since it reduces the complexity and improves the classification performance of QDF [5, 6].

Neural networks has the ability to implicitly detect complex nonlinear relationships between dependent and independent variables. It detects all possible interactions between predictor variables. Feed-forward neural networks, including multilayer perceptron (MLP) [15], radial basis function (RBF) network [16], the probabilistic neural network (PNN) [17], higher-order neural network (HONN) [18], etc., have been widely applied to pattern recognition. The connecting weights are usually adjusted to minimize the squared error on training samples in supervised learning. Using a modular network for each class was shown to improve the classification accuracy [9]. A network using local connection and shared weights, called convolutional neural network, has reported great success in character recognition [10]. Using the STEPNET [19, 21] procedure to decompose the problem into simpler sub-problems which can be solved by linear separators, a single layer neural network classifier can be used to solve complex real-world classification problems such as the recognition of handwritten digits. Neural networks have greater computational burdens. It requires lots of data to achieve an accuracy of more than 99% and also lots of processing power.

Kernel based methods, including support vector machines (SVMs) [12, 13] primarily and kernel principal component analysis (KPCA), kernel Fisher discriminant analysis (KFDA), etc., are receiving increasing attention and have shown superior performance in pattern recognition. An SVM is a binary classifier with discriminant function being the weighted combination of kernel functions over all training samples. After learning by quadratic programming (QP), the samples of non-zero weights are called support vectors (SVs). For multi-class classification, binary SVMs are combined in either one-against-others or one-against-one (pair wise) scheme [20]. Due to the high complexity of training and execution, SVM classifiers have been mostly applied to small category set problems. A strategy to alleviate the computation cost is to use a statistical or neural classifier for selecting two candidate classes, which are then discriminated by SVM [11]. Dong et al. used a one-against-others scheme for large set Chinese character recognition with fast training [14]. They used a coarse classifier for acceleration but the large storage of SVs was not avoided.

On our part, after pre-processing we will use polygon approximation to achieve a distinctive contour of the character. This is ensued by convex decomposition which segments each convex part. Each of the segmentation is then eight segment encoded for feature extraction. With accurate feature file generation we shall be able to attain more precise output in addition to less data requirement for machine training.

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