Automatic handwriting recognition using Artificial Neural Network

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Abstract

OFFLINE handwritten text recognition is one of the most active fields of computer science study, and it is intrinsically challenging due to the wide range of writing styles. Character recognition and isolated word recognition reach great recognition rates, but we are still a long way from developing high-performance recognition algorithms for unconstrained offline handwritten manuscripts. Automatic handwriting recognition systems often contain multiple pre-processing processes to decrease variance in handwritten texts as much as feasible while yet preserving information that is crucial for recognition. There is no universal approach for preparing offline handwritten text lines, although it often depends on slope and slant correction as well as letter size normalisation. Using Artificial Neural Networks, this research proposes novel strategies for removing the slope and slant from handwritten text lines and normalising the size of the text pictures (ANNs). The slope and horizontal alignment are properly estimated using local extreme from a text picture recognised as belonging to the lower baseline by a Multilayer Perceptron (MLP). ANNs are also used to eliminate slant in a non-uniform manner. Finally, another MLP calculates the slope and slant adjusted text's reference lines in order to normalise its size.

1. Introduction

The handwritten text is rotated horizontally using the slope correction such that the bottom baseline aligns with the image's horizontal axis. The slant is the angle formed between the vertical direction and the vertical text strokes when seen in a clockwise manner. The word becomes upright after slant correction. The elimination of slope and slant should, in theory, result in a word picture that is not affected by these variables.

Offline cursive word recognition is discussed in depth. We primarily discuss the various strategies presented for realising the recognition core in a word recognition system. The size and nature of the vocabulary involved, as well as whether or not a segmentation step is present, are explored in light of these methodologies.

The field may be divided into three groups: segmentation-free methods compare a sequence of observations derived from a word image with similar references of words in the lexicon; segmentation-based methods look for the best match between consecutive sequences of primitive segments and letters of a possible word.

Even with the development of new technology, handwriting has remained to be used as a mode of communicating and recording information in everyday life. Machine recognition of handwriting has practical value due to its prevalence in human transactions, such as reading handwritten notes in a PDA, postal addresses on envelopes, amounts in bank checks, handwritten fields in forms, and so on. The nature of handwritten language, how it is converted into electronic data, and the essential ideas underpinning written language recognition systems are all covered in this introduction. Both the online and offline cases are taken into account.

Character recognition (CR) has been studied extensively over the last half-century and has advanced to the point where it may be used in technology-driven applications. Now that computer power is fast expanding, current CR approaches can be implemented, and there is a growing need in many developing application sectors for more sophisticated methodologies.

2. Literature survey

Following its success in automated voice recognition, Hidden Markov Models (HMMs) have been widely used to offline handwriting recognition. Handwriting can be read as a left-to-right series of ink signals that is equivalent to the temporal sequence of auditory impulses in speech, according to the basic principle. The impetus for the work given here on hybrid HMM/ANN models comes from a review of the current state of the art in offline handwritten text recognition.

This article provides an overview of off-line Cursive Word Recognition. The methods to the problem are thoroughly discussed. Each stage of the process from raw data to final product is examined. This review is divided into two sections, the first dealing with general elements of Cursive Word Recognition and the second with applications given in the literature.

The current state of the art in off-line Roman cursive handwriting recognition is reviewed in this work. A picture of a digit, a word, or - more broadly - some text is sent as input to an off-line handwriting recognition system, and the system provides an ASCII transcription of the input as output. This work necessitates a lot of processing stages, some of which are challenging. Typically, activities like as pre-processing, normalisation, feature extraction, classification, and post processing are required. We will assess the state of the art, examine recent developments, and attempt to identify challenges for future study in this topic.

Over the last several years, significant progress has been achieved in handwriting recognition technology. Because most handwriting recognition systems rely on a lexicon throughout the recognition process, they have been confined to short and medium vocabulary applications. The capacity to cope with huge lexicons, on the other hand, offers up a plethora of new applications. This article will address the methods and ideas recommended for dealing with big vocabularies, as well as the significant concerns impacting their future adoption.

A hidden Markov model-based technique for recognising unconstrained handwritten words in huge vocabularies off-line. Following pre-processing, a word picture is segmented into letters or pseudo letters and represented by two feature sequences of equal length, each consisting of an alternating sequence of shape-symbols and segmentation-symbols, both of which are explicitly modelled.

The word model is composed of suitable letter models composed of elementary HMMs, and an HMM-based interpolation approach is utilised to best integrate the two feature sets. Depending on whether or not the word picture is guaranteed to be in the lexicon, two rejection processes are examined.

3. Methodology

The suggested method is Off-line Signature Verification Using the Enhanced Modified Direction Feature and Neural-based Classification, in which we use MDF with signature photos. Specifically, a variety of characteristics have been coupled with MDF in order to capture and analyse various structural and geometric qualities of signatures. Several stages must be conducted in order to accomplish verification or identification of a signature.

After preparing all signatures from the database by converting them to portable bitmap (PBM) format, their boundaries are removed to assist feature extraction using MDF. Verification trials are carried out using classifiers. We are employing the Radial Basis Function (RBF), a classifier with a 91.21 percent accuracy level.

- **Authentication**

Authentication is the first module of Off-line Signature Verification Using the Enhanced Modified Direction Feature and Neural-based Classification. Authentication is performed in order to protect the programme from unauthorized users. The login and password are validated, and the illegal user is dismissed. If the username and password are correct, the user can access the programme. It provides security to our application because it is the initial module of the project.

- **Preprocessing**

Preprocessing is nothing more than a procedure in which the input picture is turned into. The pbm format is a bitmap format. And submitted for further execution. The reason for converting it to bitmap format is that the bounds of the signature will be easier to extract in the second module if it is in bitmap format.

- **Feature extraction**

The signature image's boundaries are extracted using MDF (modified extraction feature) for further modification. The purpose of extracting the signatures boundaries is to make it easier for the classifier to identify and verify the signature because the size of the image is reduced during feature extraction.

- **Classification**

The input for the classification process is an image file, and the classifier validates and detects the signature. This is the project's last module, and it employs a trained classifier that has an accuracy of roughly 91.21 percent, which is significantly higher than the current system.

4. Result and discussion

The Common Type System (CTS) is used by the CLR to strongly ensure type-safety. By expressing types in a consistent manner, this guarantees that all classes are compatible with one another. CTS specify how types function within the runtime, allowing types from one language to interact with types from another, including cross-language exception handling.

The runtime guarantees that code does not attempt to access memory that has not been allocated to it, in addition to guaranteeing that types are only used in appropriate ways.The CLR has built-in language interoperability capability. A collection of language features and rules for utilising them called the Common Language Specification (CLS) has been created to ensure that you may produce managed code that can be fully used by developers using any programming language. CLS-compliant components adhere to these requirements and expose only CLS functionalities.

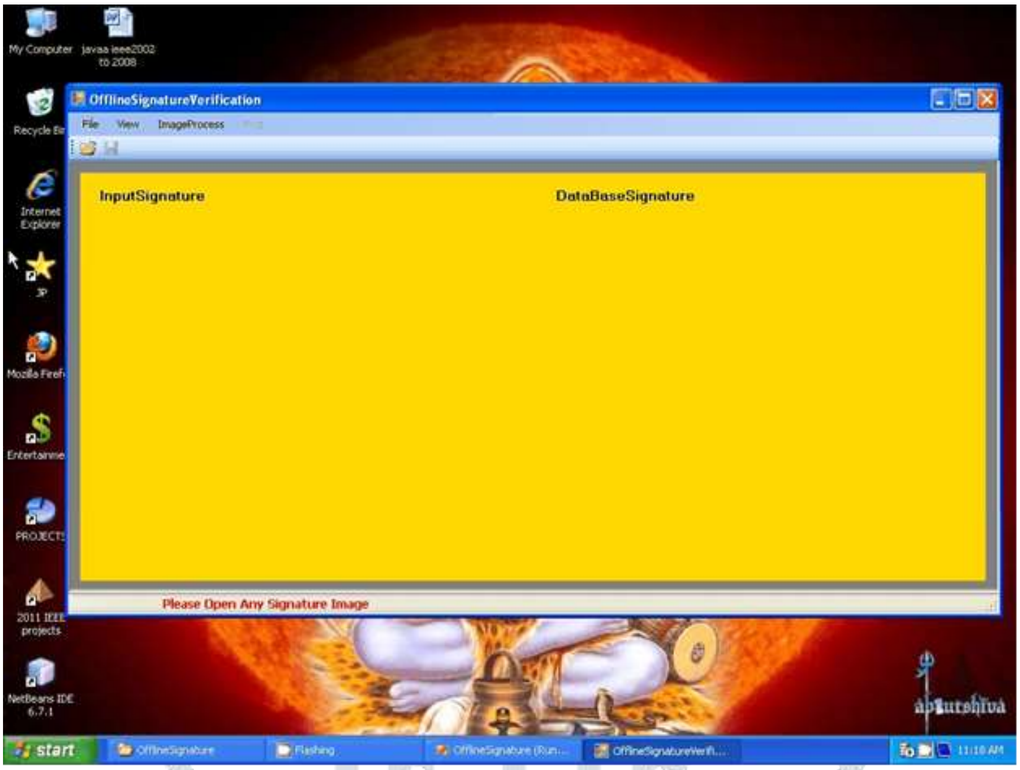

Fig.1 Opening signature image

Fig.2 Signature verification

5. Conclusion

We offer a hybrid ANN system for identifying unconstrained offline handwritten text lines in this research. The recognition system's distinguishing qualities are its new approaches to pre-processing and recognition, both of which are based on ANNs. MLPs are used to clean and enhance the pictures, automatically categorise local extreme in order to correct the slope and normalise the size of the text lines images, and execute a nonuniform slant correction. The recognition is based on hybrid optical ANN models, with the emission probabilities estimated using an MLP. The classification system is based on hybrid optical ANN models, with an MLP employed to estimate emission probabilities. The capacity of ANNs to learn complicated nonlinear input-output correlations from examples is the fundamental feature that makes them suitable for pre-processing jobs. When used for regression, an MLP may learn the proper filter from instances. We used this feature to clean and improve the text images. MLPs may be used for classification to establish the affiliation of interest points from an image to reference lines, which is important for slope correction and size normalisation, as well as to detect slant in a text image.

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