Offline Signature Verification using Siamese Neural Networks

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ABSTRACT

Handwritten signature verification is an emerging area, every person has his/her own unique signature that is used mainly for the purposes of personal identification and verification of important documents or legal transactions. There are two kinds of signature verification: online and offline. Online signatures consist of sequences of point coordinates which are followed by the pen, and they are obtained by electronic means when signing. Off-line signatures are images obtained after scanning a signed document and there is not any dynamic information from the act of signing Moreover, the off-line verification of handwritten signatures still remains a challenging open problem.in the field of the financial, commercial and for the legal matters. Signature by any person considered as the approval for any work so the signature is the preferred authentication. In this paper signature verification is done by means of image processing, feature extraction and by using neural network technique.

Keyword: - *Offline handwritten signature verification image processing, preprocessing feature extraction and Siamese Neural Networks.*

1. INTRODUCTION

The manual verification based on signatures get tougher and time consuming when there is a large number of documents. In the case of verification, the problem consists of determining the degree of similarity between a test signature and a model signature to decide whether or not this test signature is authentic or a forgery. One of the main difficulties is the interpersonal variabilities when signing, as the signatures from the same writer present variations due to the available space for signing, the type of pen used, the psycho-physical condition of the signer, and other factors.fig1 shows four different signatures produced by the same writer in different times and using different pens.

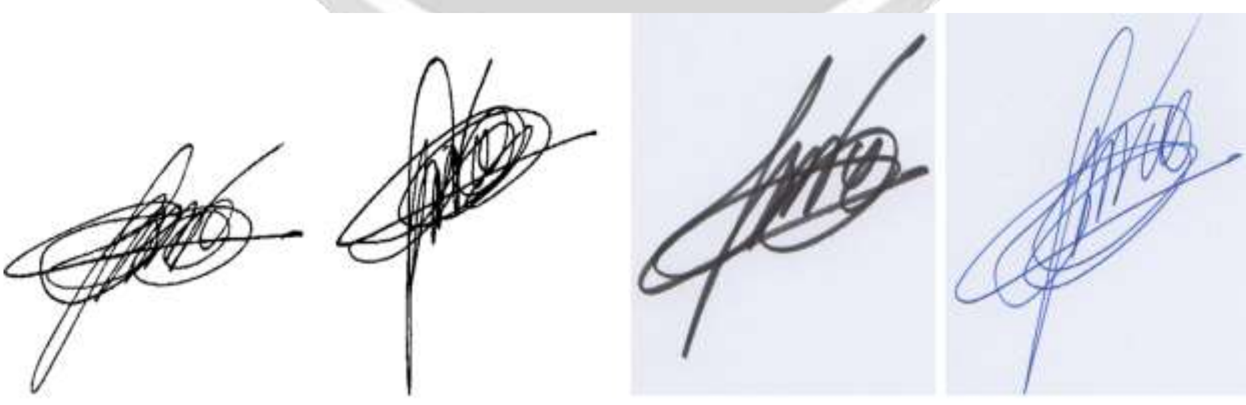

Fig1.

A signature verification system can be considered as *writer-independent* or *writer-dependent* one. In *writer-independent* systems there exists a model that does not need to be modified when new signers are added to be verified. On the contrary, in *writer-dependent* systems the model needs to be retrained when new signers are introduced.

The types of forgeries in signatures can be classified as: *skilled*, *simple* and *random* ones. For the case of *skilled* forgeries, the impostor tries to imitate a genuine signature which is known for him/her. In *simple* forgery signatures, the impostor knows the name but not the signature of the writer, so he/she invents a forgery signature expecting. to deceive the system. Finally, *in random* forgeries, the impostor knows neither the name nor the signature of the writer, so he invents a random forgery. A random forgery test is a typical test used in access control systems, commercial transactions and bank procedures

All these overloads can be reduced by automating the signature verification process by using neural network. Thus, the task of an automatic handwritten signature verification system will be to confirm the identity of a person based on his/her signature. This paper is implemented for the writer independent model for random forgeries: in this we list the main *datasets* that are available to evaluate such systems. We then describe the techniques used for each process for training a system: *Pre-processing*, *Feature Extraction* (features that can be extracted from the trace of the static signature images.) and *model training* and potential areas for future research.

2. MATERIAL AND METHODS

2.1 Dataset

we have analysed two types of synthetic data to increase the number of samples and the variability needed for training deep neural networks: augmented data samples from GAVAB dataset and GPDS Synthetic dataset. In our approach, we initially trained Siamese Neural Networks using signatures from GAVAB dataset and different combinations of synthetic data.

2.2 Preprocessing

In order to prepare the signatures for the verification stage we perform a preprocess to all training and test images. On the one hand, these preprocessing aims to scale the signatures to a fixed size. On the other hand, normalization tries to homogenize the input signatures from different datasets.

2.3 Augmentation

Data augmentation techniques are used to increase the dataset size for neural network training. With this technique, pairs of genuine/forgery signatures are generated. Then, some compositions of transformations are applied while the model is training, so a pseudo-infinite number of signature samples is created.

2.4 Feature Extraction

It is one of the important modules for image processing. In this stage we compute features of an image which results in recognition accuracy with very simple classification module. Some of the generic features are:

(a) Morphological features focusing on the shape attributes. Some of the standard feature extractions under morphological features are: width and height.

(b) Zernike features: These features help in representing properties of an image with no overlap and to describe shape characteristics.

(c) Shape features: These include measuring the similarities between shapes represented by their features. Some of the shape parameters are area, eccentricity, perimeter etc.

2.5 Signature verification using a Siamese Neural Network

To perform the signature verification process, we propose a Siamese Neural Network (SNN). In many cases, these networks are used to compare two input images. SNN are composed by two twin networks, with the same weights joined by a distance metric. One twin receives a genuine model signature and the other one receives a signature to be verified against the model one. Then, each twin makes a feature extraction based on its corresponding input. Finally, the difference of the extracted features by the twins is calculated by a distance metric in the last output layer. During the training, the subsets of positive and negative samples (i.e. genuine and forged signatures) were balanced. However, in the test stage there were more negative samples than positive ones. This is because in tests, each original signature is compared to all of the other original signatures in the test dataset. Best results were achieved when our model was trained using a combination of real, augmented signatures.

3.RESULT

After the execution we produced a final signature verification model based on Siamese Neural Networks, referred as SCINN. Best results were achieved when our model was trained using a combination of real, augmented and synthetic signatures. Using this trained model, an 4.9% of Equal error rate(EER) was achieved on the test samples. It is important to remark that our solution is writer-independent, which makes it more difficult to reduce the EER than in the writer-dependent case. Moreover, the large inter-class and intra-class variabilities, present in test signatures, also made the reduction of the EER value difficult.

4.CONCLUSIONS

We have described an effective approach for the offline signature verification problem against random forgeries. We developed a writer-independent system based on a Siamese Neural Network architecture. The achieved accuracy results of our model, when training and testing with different datasets, made it usable for new signers without any additional training stage.

5. REFERENCES

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