Offline Signature Verification Using Feature Learning and One-Class Classification

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Abstract. Offline signature verification remains the most commonly employed authentication modality and enjoys global acceptance. From the viewpoint of computerized verification, concluding the authenticity of a signature offers a challenging problem for the pattern classification community. A major proportion of computerized solutions treat signature verification as a two-class classification problem where both genuine and forged signatures are employed for training purposes. For most of the real-world scenarios however, only genuine signatures of individuals are available. This paper presents a signature verification technique that relies only on genuine signature samples. More precisely, we employ convolutional neural networks for learning effective feature representations and a one-class support vector machine that learns the genuine signature class for each individual. Experiments are carried out in a writer-dependent as well as writer-independent mode and low error rates are reported by only employing genuine signatures in the training sets.

Keywords: Feature learning · One-class classification · Signature verification · Forgery detection

1 Introduction

Authenticating the claimed identity of an individual is a critical requirement in many practical scenarios including security systems, financial transactions and legal documents. In most cases, such systems rely on biometric technology exploiting either physical (such as face, fingerprint, iris etc.) or behavioural characteristics (such as voice, signature, handwriting, gait etc.) [13] to authenticate a person. Despite the technological advancements in DNA or fingerprint based authentication, signature remains the most commonly used mode of verification due to its ease of acquisition and global acceptability.

Signatures are handwritten and hence they may contain symbols, different slants and varying writing styles. In general, it is common for individuals to develop signatures which are distinct and hard to copy by others [24].

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Forgers, however, can mimic the signature of an individual by practising it to perfection. Signature forgery refers to imitating someone else’s signature in an attempt to claim their identity. Signature forgeries are typically classified into three classes namely random forgery, unskilled forgery and skilled forgery [15,22]. Random forgery refers to the scenario in which the forger has not seen the genuine signature and produces a random signature pretending to be the authorized individual. The term unskilled forgeries refers to the situation when the forger has the knowledge of only the name not the signature of the individual. The most challenging is to identify the skilled forgery where the forger has complete knowledge of the signature of claimed identity and the signatures are practised repeatedly prior to the forgery attempt.

Depending on the mode of acquisition, signature verification techniques are classified into online and offline methods [15,36]. Online signatures are typically captured using devices like optical pens and touch sensitive tablets. Such devices allow capturing the dynamic characteristics of a signature including attributes like pen pressure, writing speed, number and order of strokes, etc. Offline signatures, on the other hand, refer to digitized images of signatures captured using a camera or scanner [20,23]. From the view point of verification technique, systems that rely on training a separate model for each individual to verify the signature are known as Writer-dependent (WD) systems. Writer-independent (WI) systems, on the other hand, train only one model for all individuals to differentiate between genuine and forged signatures [15].

Research in signature verification has matured progressively over decades. Deep learning has emerged as a revolutionary and state-of-the-art framework for data driven feature learning and classification [7] in the recent years. Convolutional Neural Networks (CNNs) for example, have been applied for effective feature learning in many problems including handwriting recognition [27,32], writer identification [5,40] and signature verification [17,39].

In this work, we employ both WI and WD feature learning approaches using a deep CNN and validate the effectiveness of learned feature representations using WI and WD One-class Support Vector Machine (OCSVM). The CEDAR dataset and the ICDAR 2015 Competition dataset on Signature Verification and Writer Identification for On-line and Off-line Skilled Forgeries (SigWcomp2015 Italian signatures) [21] are used for the evaluation of the proposed approaches. Three different combinations of feature learning and OCSVM are employed. These include WD feature learning with WD OCSVM, WI feature learning followed by WD OCSVM and, WI feature learning followed by WI OCSVM. The experimental study reveals low error rates despite we only used genuine signatures in the training set. This study reveals that proposed feature learning approach is robust in WI as well as WD mode.

The rest of the paper is structured as follows. An overview of significant contributions to offline signature verification is presented in Sect. 2. Section 3 introduces the datasets which have been utilized in our study while Sect. 4 details the proposed feature learning and classification technique. Experimental protocol
and the reported results along with a discussion are presented in Sect. 5. In the end, we summarize the key findings in Sect. 6 and conclude the paper.

2 Related Work

Signature verification has been an active research direction for forensic experts, document examiners, and computer scientists for decades now. A number of comprehensive surveys covering both offline and online signature verification systems have also been published from time to time [30,34,36]. In general, offline signature verification is considered more demanding as compared to online signatures as only the final shape of signature image is available in case of offline images [20]. Nevertheless, offline signatures enjoy wider acceptability due to the simplicity in acquisition.

Features for verification of signature can be structural or statistical and are computed either locally (from parts of signature) or globally (from complete signature image). In some cases various features are combined to enhance the overall verification performance. In many cases, geometrical features, such as ratios of interest, information on loops and endpoints [10,15], have been effectively employed for verification of signatures. In addition to key geometric ratios, symmetry of the signature, angular displacement to a horizontal baseline and spacing etc. [29] are also considered. A number of transforms have also been investigated to characterize signatures. These include Heden transform [26], Contourlet transform [31], Discrete Radon transform [6] and Fractal transform [43]. Similarly, textural measures like Local Binary Patterns (LBP) and Histogram of Oriented Gradients (HOG) have also been employed in various studies [2,41]. From the view point of classifiers, Hidden Markov models (HMM) [19], Support vector Machine (SVM) [18], Neural networks (NN) [33] and ensemble method [3] etc. have been commonly employed.

With the advent of deep learning, the classical pipeline of hand-engineered feature extraction followed by classification is being replaced by data driven feature extraction and classification as an end-to-end learning systems. In some cases, it is also common to employ deep learning techniques as feature extractors only and employ traditional classifiers for classification. Among notable contributions exploiting deep neural networks, Nam et al. [25] present a CNN based feature representation with an autoencoder as classifier to distinguish between genuine and forged signatures. Likewise, Saffar et al. [35] employ autoencoders with one-class classifier for drawing hyper-spheres around genuine signatures (projected in the feature space) to distinguish them from the forged ones.

In a series of related studies by Hafemann et al. [11,12,14], CNN based feature learning has been thoroughly investigated. In [14] for instance, a two-step approach is presented where feature learning is first carried out in a writer-independent mode while the classification is carried out in a writer-dependent framework using binary SVM. The feature learning model was trained using GPDS-960 dataset and was used to extract features for GPDS-160, GPDS-300, MCYT, CEDAR and Brazilian PUC-PR datasets. A number of other related
studies [37, 39] also demonstrate the superiority of machine learned over hand-designed features for signature verification. Dutta et al. in [9] computed Compact correlated features in WI mode and verification was performed using Euclidean distance between pairs of signatures for CEDAR and GPDS300 dataset. In another study, Dey et al. employed a WI siamese Convolutional network for verification and calculated a joined loss function. They evaluated the approach on CEDAR, GPDS300, BHSIG260 and GPDS Synthetic dataset [8]. In our study, we also investigate machine learned features to characterize the signature of an individual, details presented later in the paper. Only genuine signatures for feature learning as well as for verification are used for training which resembles the real life scenario which was not the case in above mentioned approaches. In contrast to previous studies, proposed approach is applicable to both WI and WD settings.

3 Datasets

We employ two datasets (which are publicly available) for the experimental evaluation of our proposed system. These include the CEDAR signature dataset [1] and the SigWIComp2015 Italian signature dataset (SigWIComp2015 [21]). The CEDAR dataset\(^1\) has 24 genuine samples and 24 skilled forgeries for 55 different signers. Out of these, 12 genuine signatures of each user are used to train the CNN(s) and subsequently the feature vectors of these signatures are employed to train the OCSVM. The remaining 12 genuine signatures and 24 skilled forgeries per user are treated as the test set. The SigWIComp2015 Italian signature dataset\(^2\) has 50 individual signers with a total of 485 genuine and 249 forged samples. The detailed distribution of signatures into training and test sets for both datasets is presented in Table 1.

4 Proposed Methodology

The proposed Methodology for verification of signatures rests on two key components, i.e., feature learning using a ConvNet and verification using a OCSVM. Feature learning and verification are carried out in WI as well as WD modes. An overview of the key processing steps is presented in Fig. 1 while the details of these steps are presented in the following section.

4.1 Feature Learning Using CNN

A typical CNN is a pile of convolutional and sampling layers with some fully connected layers at the end. Convolution operation is the core of a CNN which allows learning robust features (filters) through back propagation. The architecture of the CNN employed in our study is illustrated in Fig. 1-b while the details

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\(^1\) Download Dataset: http://www.cedar.buffalo.edu/NIJ/data/signatures.rar.

\(^2\) Download Dataset: http://tc11.cvc.uab.es/datasets/SigWIComp2015_1.
Table 1. Division of datasets into training and test set

| Dataset                  | Authors | Dataset division | Genuine/author | Forged/author | Total |
|--------------------------|---------|------------------|----------------|--------------|-------|
| CEDAR                    | 55      | Training         | 12             | 0            | 660   |
|                          |         | Test             | 12             | 24           | 1980  |
| SigWiComp2015 Italian    | 50      | Training         | 4 or 5         | 0            | 256   |
|                          |         | Test             | 4 or 5         | 5            | 478   |

Fig. 1. Overall flow of methodology

are presented in Table 2. These details include the size and number of filters at each convolutional layer, hyper-parameters for the pooling layers and the size of feature map at each layer. All Conv layers employ the ReLu activation function while the last fully connected layer employs sigmoid activation with a single neuron. Stochastic gradient descent is used as optimizer with a decay rate of $10^{-4}$ and learning rate of $10^{-3}$. The model is trained (until convergence) with a batch size of 4.

The model learns a function $\phi(\cdot)$ which can project data $X$ to a new feature space $\phi(X) \in \mathbb{R}^b$ where $b$ is the size of feature vector. Once the CNN is trained, it is used to extract feature representation for each signature in the training and test sets. The size of feature vector in our case is 2096 which is the number of neurons in the fully connected layer before the last sigmoid layer. The training set feature vectors are used to train the OCSVM and test set feature vectors are used for evaluating OCSVM.

The CNN is trained in WI and WD modes using only genuine samples of the individuals under study. Training the CNN in each of the two modes is discussed in the following.
### Table 2. Details of proposed architectural of the CNN

| Layer | Type       | Output shape | Kernel size | Stride | Number of filters |
|-------|------------|--------------|-------------|--------|------------------|
| 1     | Convolution| $80 \times 530 \times 90$ | 7           | 1      | 90               |
| 2     | MaxPooling | $40 \times 265 \times 90$  | 2           | 2      | –                |
| 3     | Convolution| $40 \times 265 \times 228$ | 5           | 1      | 228              |
| 4     | MaxPooling | $20 \times 132 \times 228$ | 2           | 2      | –                |
| 5     | Convolution| $20 \times 132 \times 350$ | 3           | 1      | 350              |
| 6     | Convolution| $20 \times 132 \times 284$ | 3           | 1      | 284              |
| 7     | Convolution| $20 \times 132 \times 326$ | 3           | 1      | 326              |
| 8     | MaxPooling | $10 \times 66 \times 326$  | 2           | 2      | –                |
| 9     | Convolution| $10 \times 66 \times 360$  | 3           | 1      | 360              |
| 10    | MaxPooling | $5 \times 33 \times 360$   | 2           | 2      | –                |
| 11    | Convolution| $5 \times 33 \times 394$   | 3           | 1      | 394              |
| 12    | MaxPooling | $2 \times 16 \times 394$   | 2           | 2      | –                |
| 13    | Convolution| $2 \times 16 \times 275$   | 3           | 1      | 275              |
| 14    | Flatten    | 8800         | –           | –      | –                |
| 15    | Dense      | 2096         | –           | –      | –                |
| 16    | Sigmoid    | 1            | –           | –      | –                |

**Writer-Independent Feature Learning.** In WI feature learning, genuine signatures of all users in the training set are fed to a single CNN for training. Once the CNN model is trained, all the test samples are fed to CNN to carry out feedforward propagation through the network and feature representation is obtained from activations at last fully connected layer before sigmoid layer. Then the extracted features for training and test set are fed to OCSVM for training and classification, respectively.

**Writer-Dependent Feature Learning.** WD feature learning involves training a separate model for each writer under study. A separate CNN is trained with genuine signature images of each individual in the dataset. The models are then employed to extract features for all signatures in the training and test sets from the respective CNN.

### 4.2 One-Class Classification Using SVM

Once features are computed using trained CNN model(s), we need to train a classifier to learn to identify the genuine signatures of an individual. As discussed previously, in real life scenarios, forged samples are not available for most of the practical signature verification applications. Instead, we may have multiple samples of an individual’s genuine signatures. Signature verification problem can hence be modeled as a one-class problem where we have only positive samples
for training and no negative samples. One-class classification can be viewed as an attempt to find a (hyper)sphere boundary with a specific radius around the positive samples. When a questioned sample is received, it is projected in the feature space and the distance of the sample from the origin is computed. If the sample lies within the boundary of the genuine class, it is identified as a positive sample, otherwise, it is identified as a negative sample (forged signature).

We have used OCSVM as classifier, the hyper sphere has the center $a$ and radius $R > 0$, which is the distance from origin to the class boundary for which we will minimize $R^2$. The key parameters for OCSVM are kernel type, $gamma$ and $nu$ where kernel type is either ‘linear’ or ‘rbf’, $gamma$ is the kernel coefficient for ‘rbf’ kernel and $nu$ is the upper bound on the fraction of training errors and a lower bound on the fraction of support vectors. Similar to feature computation, we investigate WI and WD OCSVMs for verification.

**Writer-Independent One Class Support Vector Machine.** For writer-independent OCSVM, features from training images of all users are used to train a single OCSVM. During evaluation, the remaining genuine samples and skilled forgeries of all the users are used. The normalized scores for each sample are computed and used for calculating evaluation metric Equal error Rate (EER).

**Writer-Dependent One Class Support Vector Machine.** For writer-dependent OCSVM, features from training data of each individual are used to train a separate OCSVM for each user. Subsequently, the genuine and forged samples in the test set of each individual are employed to evaluate the respective OCSVM.

**Table 3.** Different experimental settings for feature learning and classification

| Exp. setting | Feature learning | OCSVM |
|--------------|-----------------|-------|
| Scenario I   | WD              | WD    |
| Scenario II  | WI              | WD    |
| Scenario III | WI              | WI    |

**Table 4.** Equal Error Rates for the three experimental scenarios, with standard deviation in parenthesis

| Scenario                  | Dataset          | CEDAR   | SigWiComp2015 |
|---------------------------|------------------|---------|---------------|
| WD CNN + WD OCSVM        |                  | 0.00 (±0.00) | 0.27 (±1.35) |
| WI CNN + WD OCSVM        |                  | 0.00 (±0.00) | 0.27 (±1.92)  |
| WI CNN + WI OCSVM        |                  | 0.00     | 0.53          |
5 Experiments and Results

The experimental protocol and the reported results are presented in this section. We first introduce the evaluation metric followed by experimental settings and then discuss the performance of the learned features with OCSVM. Finally, a comparative overview of notable signature verification techniques is presented.

For quantization of system performance, we employ the well-known Equal Error Rate (EER) that is computed using the False Acceptance Rate (FAR) and the False Rejection Rate (FRR). The FAR is the percentage of forged signatures identified as genuine while FRR is the percentage of genuine signatures mistakenly rejected as forged. Typically, FAR and FRR are computed by varying the decision threshold and EER refers to the value when FAR equals FRR.

In SigWiComp2015, the metric of cost of log-likelihood ratio, \( \hat{Cllr} \), and its minimum value, i.e., \( \hat{Cllr}_{\text{min}} \) were computed in order to benchmark the performance of the participating systems. \( \hat{Cllr} \) is calculated from Eq. 1:
\[
\hat{Cllr} = \frac{1}{2 \times \log 2} \left[ \frac{1}{N_0} \sum_{i=1}^{N_0} \left( 1 + \frac{1}{LR_i} \right) + \frac{1}{N_1} \sum_{i=1}^{N_1} (1 + LR_i) \right] \tag{1}
\]

Where \( N_0 \) are the number of genuine signatures of the reference author, \( N_1 \) are the number of forged signatures of the reference author, \( LR \) is the likelihood ratio of genuine signatures and \( LR_1 \) is the likelihood ratio of forged signatures. The detail of computing \( \hat{Cllr} \) is given in [4]. \( \hat{Cllr}_{\text{min}} \) is computed by adjusting likelihood ratios (LR) using a logistic function. This metric not only computes the error rate, but it also consider the severity of errors made by a system. The severity of errors, in particular, is important in case of biometric and other forensic systems where a minor error can lead to loss of life. Please note: the smaller the value of \( \hat{Cllr}_{\text{min}} \), the better the system [21].

System evaluation is carried out using three different settings as a function of WI and WD modes for feature learning and classification. These settings are summarized in Table 3 while the EER values for each of these settings for the two datasets are presented in Table 4. It can be observed that error rates on CEDAR dataset are 0 for all three scenarios. Comparing the three scenarios on the SigWiComp2015 dataset, writer dependent and writer dependent feature learning reports a relatively lower error rate (0.27) when using a separate OCSVM model for classification. Using a single OCSVM for all users (WI OCSVM) reports an error rate of 0.53%. It is evident from the results, that the methodology generalizes well on both datasets.

An overview of notable signature verification techniques evaluated using the CEDAR dataset is presented in Table 5 where it can be seen that we report an EER of 0 for all three experimental scenarios and without using any forged signatures in the training set. Among other studies, Dutta et al. [9] and Dey et al. [8] also report an EER of 0 But they have used genuine and forged signatures pairs for training.

Table 6 presents the comparison of results among the system which were submitted in competition with the proposed method. The proposed system reports
| Study                              | Approach                          | Method                                         | No. of reference signature genuine/forged | EER (%) |
|-----------------------------------|-----------------------------------|-----------------------------------------------|------------------------------------------|---------|
| Hafemann et al. [14]              | WI features + WD classifier       | CNN + SVM                                     | 12/12                                    | 4.63    |
| A. Hamadene and Y. Chibani [16]   | Statistical features + WI classifier | Directional code co-occurrence matrix + Feature Dissimilarity measure (FDM) | 3/0, 4/0, 5/0                           | 3.12    |
| Okawa and Manabu [28]             | Local descriptors + WI classifier | BoVW with KAZE features + SVM                 | 16/16                                    | 1.6     |
| M. Sharif et al. [38]             | geometrical features + WD classifier | Genetic algorithm + SVM                      | 5/0, 10/0, 12/0                        | 10.41   |
| Zois et al. [42]                  | Local features + WD Classifier    | Grid based features + Binary SVM              | 5/0, 10/0                               | 3.12    |
| Dutta et al. [9]                  | Local features + WI Classifier    | Compact correlated features + SVM             | 276 pairs of gen-gen & gen-forged each   | 0.00    |
| Dey et al. [8]                    | WI features + Distance measure    | Convolutional Siamese Network + Euclidean Distance | 276 pairs of gen-gen & 276 pairs of gen-forged pairs | 0.00    |
| Proposed method                   | WD features + WD one-class classifier | CNN + OCSVM                                  | 12/0, 0, 0                             | 0.00    |
Table 6. Comparison of results with the SigWiComp2015 participants

| System       | Participant       | $\hat{Cllr}$  | $\hat{Cllr}_{min}$ |
|--------------|-------------------|----------------|--------------------|
| 1            | Proposed          | 0.324723       | 0.013465           |
| 2            | Sabanci University| 0.655109       | 0.021318           |
| 3            | Tebessa University| 0.993138       | 0.893270           |
| 4            | Tebessa University| 1.065696       | 0.952499           |
| 5            | Tebessa University| 1.074474       | 0.880930           |
| 6            | Tebessa University| 1.065475       | 0.901003           |
| 7            | Tebessa University| 1.041895       | 0.901003           |
| 8            | Qatar University  | 8.901864       | 0.972708           |
| 9            | Qatar University  | 13.111064      | 0.960163           |
| 10           | Commercial System | 1.003786       | 0.988845           |

A $\hat{Cllr}$ value of 0.324723 and $\hat{Cllr}_{min}$ equal to 0.013465 which outperforms all the systems which were proposed in competition.

6 Conclusion

In this study, we investigated the offline signature verification problem and employed feature learning to seek robust feature representations for signature images. Features are extracted in a writer-dependent as well as writer-independent mode. For verification, we employ one-class SVM that is trained using genuine samples only to match the real world scenarios. The technique is validated on two benchmark datasets and low error rates are reported.

In our further study on this subject, we aim to investigate the performance of one-class classification on other common datasets. Furthermore, feature learning using recurrent neural networks rather than convolutional networks is also being experimented.

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