Universidade de Pernambuco - UPE
Escola Politécnica de Pernambuco - POLI
Mestrado em Engenharia da Computação

A Deep Learning Approach to Generate Offline Handwritten Signatures Based on Online Samples

Victor Kléber Santos Leite Melo
vkslm@ecomp.poli.br

Advisor: Prof. Dr. Byron Leite Dantas Bezerra
Co-Advisor: Prof. Dr. Giuseppe Pirlo

August 28, 2017

Hello everyone. My Name is Victor and I am glad to present you my master's degree project. I was advised by professor Byron and Co-advised by professor Giuseppe Pirlo, from University of Bari, Italy.

The title of the work is: "A Deep Learning Approach to Generate Offline Handwritten Signatures Based on Online Samples"

This project is an application of Deep Learning on the Biometric Technology field, specifically on the signature verification field.

Universidade de Pernambuco - UPE
Escola Politécnica de Pernambuco - POLI
Mestrado em Engenharia da Computação

A Deep Learning Approach to Generate Offline Handwritten Signatures Based on Online Samples

Victor Kléber Santos Leite Melo
vkslm@ecomp.poli.br

Advisor: Prof. Dr. Byron Leite Dantas Bezerra
Co-Advisor: Prof. Dr. Giuseppe Pirlo

August 28, 2017

Hello everyone. My Name is Victor and I am glad to present you my master's degree project. I was advised by professor Byron and Co-advised by professor Giuseppe Pirlo, from University of Bari, Italy.

The title of the work is: "A Deep Learning Approach to Generate Offline Handwritten Signatures Based on Online Samples"

This project is an application of Deep Learning on the Biometric Technology field, specifically on the signature verification field.

Introduction

- Biometric technology is used in several security applications for authentication.
- **Bio** = “life” + **metriks** = “to measure”

(a) Fingerprint (b) Iris (c) Handwritten Signature (d) Voice

Figure 1: Some biometric traits used for person authentication.

Biometric techonology is used in several security applications for person authentication.

The word BIOMETRICS is derived from the GREEK - where bio means life and metriks means to measure.

A Biometric Identifier is “A UNIQUE MEASURABLE CHARACTERISTIC USED TO DISTINGUISH AND DESCRIBE INDIVIDUALS”

The aim of those systems is to confirm the identity of a given subject based on **PHYSIOLOGICAL or BEHAVIORAL** traits. **NEXT SLIDE**

*** In **PHYSIOLOGICAL** biometric systems, the reconigiton is based on MEASUREMENTS OF THE BODY such as fingerprint, IRIS, face, DNA, and so on. On the other hand **BEHAVIORAL** biometrics are traits acquired by an individual, those are related to the voice pattern, typing rhythm and handwritten signatures.

Introduction

- Biometric technology is used in several security applications for authentication.
- **Bio** = “life” + **metriks** = “to measure”

(a) Fingerprint (b) Iris (c) Handwritten Signature (d) Voice

Figure 1: Some biometric traits used for person authentication.

Biometry Categories

- Physiological - biological characteristics such as fingerprint, palm print, iris, face.
- Behavioral - individual acquired traits such as voice pattern and handwritten signature.

Biometric techonology is used in several security applications for person authentication.

The word BIOMETRICS is derived from the GREEK - where bio means life and metriks means to measure.

A Biometric Identifier is “A UNIQUE MEASURABLE CHARACTERISTIC USED TO DISTINGUISH AND DESCRIBE INDIVIDUALS”

The aim of those systems is to confirm the identity of a given subject based on **PHYSIOLOGICAL or BEHAVIORAL** traits. **NEXT SLIDE**

*** In **PHYSIOLOGICAL** biometric systems, the reconigiton is based on MEASUREMENTS OF THE BODY such as fingerprint, IRIS, face, DNA, and so on. On the other hand **BEHAVIORAL** biometrics are traits acquired by an individual, those are related to the voice pattern, typing rhythm and handwritten signatures.

Handwritten Signature

Figure 2: Handwritten Signatures are a widespread biometry.

The Handwritten Signature stands as one of the primary methods for identity authentication. This biometric trait can be considered the most legally and socially accepted attributes for person identification.

In the picture we can see the signature being performedin in a business contract, next using a special kind of digitizing tablet and also on a mobile device, that is an application that is being studied in the field recently.

Handwritten Signature (2)

The Handwritten Signature widespread can be attributed to[1]:

- Signature acquisition is easy and non-invasive;
- Most individuals are familiar with its use in their daily life;
- Signatures can be employed as a sign of confirmation in a wide variety of documents, namely, bank checks, identification documents and a variety of business certificates and contracts.

[1] Donato Impedovo and Giuseppe Pirlo (2008). "Automatic signature verification: the state of the art". In: *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)* 38.5, pp. 609–635.

Some of the reasons for handwritten signatures being one of the most widespread biometry, is that **The Signature acquisition is easy and non-invasive**

While most of the biometric identifiers require a special type of device for the identification, handwritten signature based authentication can be performed requiring no sensor except a pen and a piece of paper.

Due to its convenient nature, most of individuals are familiar with its use in their daily life and Signatures can be employed as a sign of confirmation in a wide set of documents

For instance, Bank checks, identification documents and a variety of business certificates and contracts.

Overview of a Handwritten Signature Verification System

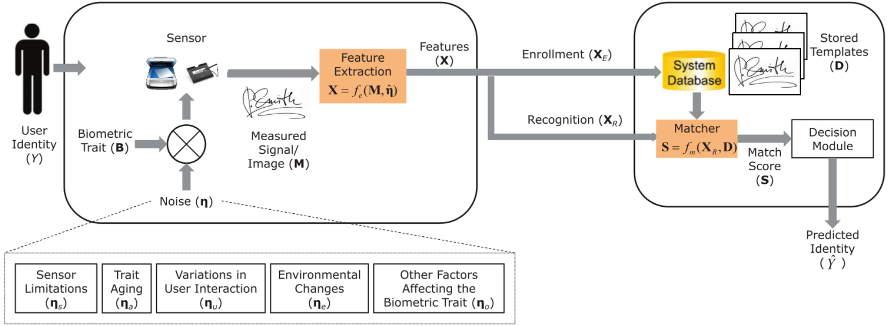


Figure 3: Overview of a typical handwritten signature based system. Figure adapted from (Jain, Nandakumar, and Ross, 2016)[2].

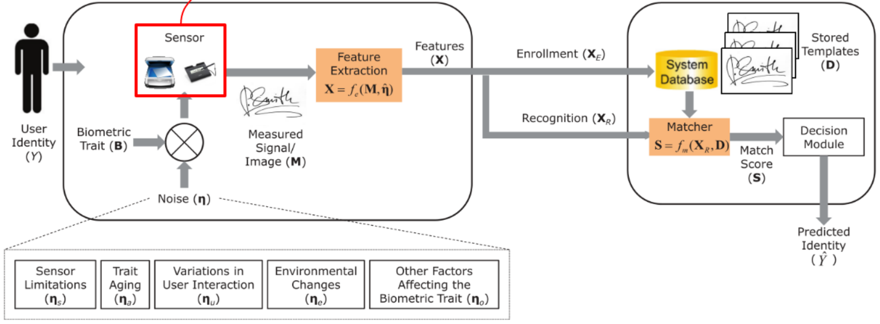
[2] Anil K Jain, Karthik Nandakumar, and Arun Ross (2016). "50 years of biometric research: Accomplishments, challenges, and opportunities". In: *Pattern Recognition Letters* 79, pp. 80–105.

This figure gives an overview of how a signature-based biometric system works.

At first, we can see that user **Y** deposits his **BIOMETRIC TRAIT B**, in this case a signature, on the system.

Overview of a Handwritten Signature Verification System

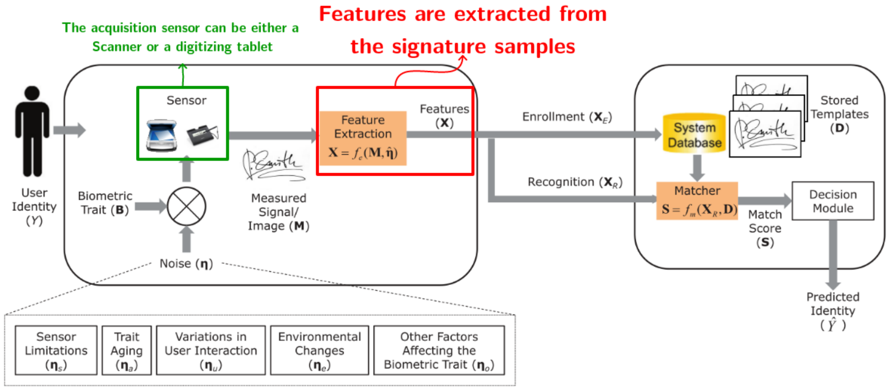
The acquisition sensor can be either a Scanner or a digitizing tablet



If the signature was made on a piece of paper, the signature is inputted to the system using an optical scanner

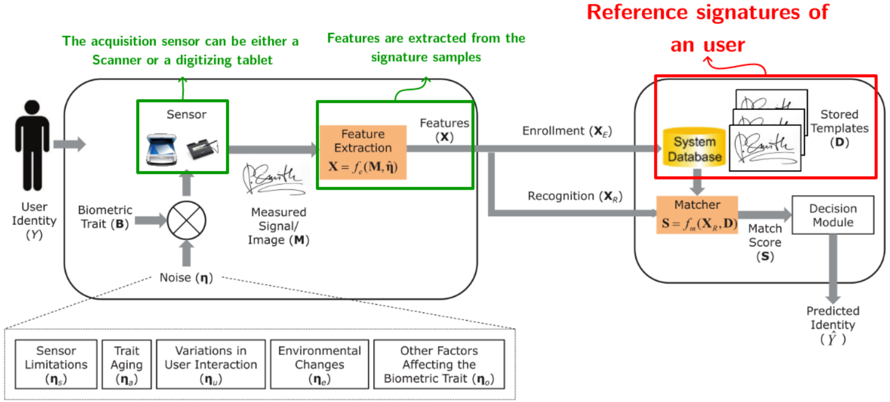
The signatur can also be performed and acquired on a digitzing tablet or a smartphone.

Overview of a Handwritten Signature Verification System



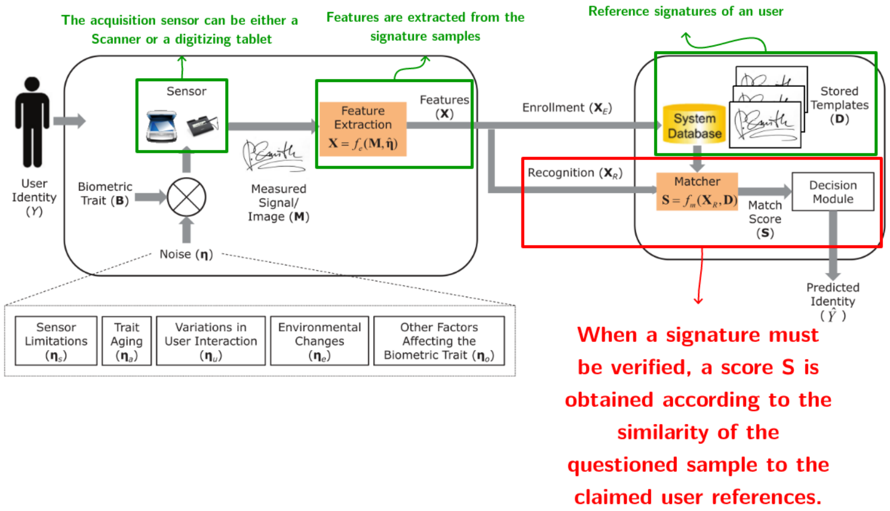
Next, the system extracts features from the signature sample, represented by the **X** on the picture.

Overview of a Handwritten Signature Verification System



Then, those features are used to build a database, or a knowledge base, to store the genuine references of the signature of the user.

Overview of a Handwritten Signature Verification System



When the system must verify a questioned signature, a score **S** is obtained according to the similarity of the questioned sample to the reference dataset. The output of the system is either positive (meaning genuien sample) or negative (meaning a fraud).

Overview of a Handwritten Signature Verification System

As we can see, a Signature Verification system is essentially a Pattern Recognition application.

As any Pattern Recognition System, a Signature Verification system has three phases:

- Data acquisition and preprocessing;
- Feature extraction;
- Classification.

As we can see, a Signature Verification system is essentially a Pattern Recognition application.

As any Pattern Recognition System, a Signature Verification system has three phases: Data acquisition and preprocessing; Feature extraction; Classification.

Online vs Offline Handwritten Signatures

OFFLINE -> STATIC

An optical scanner is used to obtain the signature directly from the pen on the paper, and only the digital image of the signature is available.

ONLINE -> DYNAMIC

Data is stored during the writing process and consists of a temporal sequence of the three-dimensional coordinates (x, y, p) of consecutive points.

(a) A signature scanned from paper

(b) Digitizing tablet Wacom STU-500

Figure 4: Different signature acquisition methods.

The signature acquisition sensor can be either an optical scanner or an acquisition device such as a digitizing tablet.

These two kinds of acquistion methods characterize the two types of signatures: STATIC, offline, AND DYNAMIC, ONLINE

In the offline modality, an optical scanner is used to obtain the signature directly from the paper and only a digital image of the signature is available

In the online modality, the data is acquired during the signing process and consists of a temporal sequence of the three-dimensional coordinates x, y, p of consecutive points

Online vs Offline Handwritten Signatures (2)

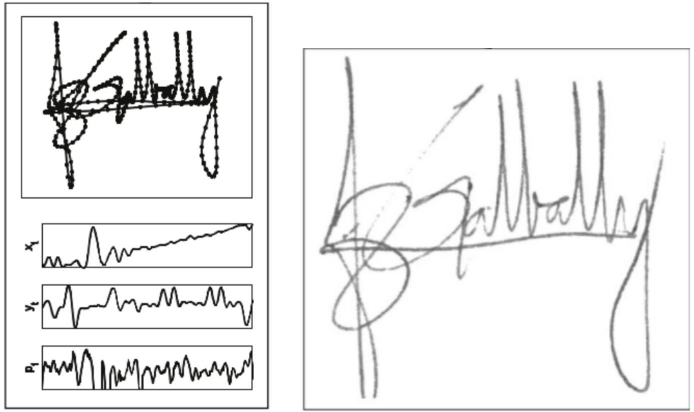


Figure 5: An online and the respective offline signature sample. Extracted from (Galbally et al., 2015)

In this image, we can see how both modalities are represented

The online signature can be thought as a three dimensional time-series,

Meaning that it is the coordinates x, y and pressure over the time.

While the offline signature is a 2D grayscale (or black and white) digital image.

Handwritten Signature Intra-personal variability

Figure 6: Superimposed genuine signatures of the same writer. A high intra-personal variability can be noticed. Extracted from (Hafemann, Sabourin, and Oliveira, 2015).

As a behavioral trait, signatures present a high intra-personal variability, that is a high similarity between signatures executed by the same writer.

there are a variety of human and social aspects that might affect the way we produce our signatures... it might be influenced by sensor limitations, biological aging effects, user emotional state

This variability must be taken into account in the authentication process.

It is one of the most challenging aspects of signature verification.

Handwritten Signature Inter-personal variability

The first column of signatures are genuine references, the following three samples are questioned signatures [3]. Signature images extracted from (Ortega-Garcia et al., 2003).

[3] From left to right, top to bottom (F means Forgery and G means Genuine): FGF FFG GFF

Another challenge faced on signature verification systems is the inter-personal variability... **The similarity between different writers**. This variability is mainly related to malicious people trying to fraud the identity of signers. **talk about the image**

Forgeries are usually classified in two types: Random forgeries and Skilled Forgeries...

Random forgeries: The forger does not attempt to simulate or trace a genuine signature, he tries to verify the identity of a person using his own signature..

On the other hand, a skilled forgery, is made by a forger that tries and practices to imitate as closely as possible the genuine signature model.

Data in Signature Verification

The amount of samples used for training the signature verification system effects the system's performance.

As any Pattern Recognition problem, the bigger the dataset, the better the system's performance.

However, in the signature verification context:

- The amount of data available for each user is often insufficient in real applications;
- During the enrollment phase, users are often required to supply only a few samples of their signatures;
- Acquisition and distribution of real signatures arise legal and privacy concerns;

The amount of samples used for training the signature verification system effects the system's performance. As any Pattern Recognition problem, the bigger the dataset, the better the system's performance.

However, in the signature verification context some points have to be considered:

The amount of data available for each user is often insufficient in real applications;

During the enrollment phase, users are often required to supply only a few samples of their signatures;

Acquisition and distribution of real signatures arise legal and privacy concerns;

Therefore, the use of realistic synthetic signatures could be regarded as a good alternative.

Data in Signature Verification

The amount of samples used for training the signature verification system effects the system's performance.

As any Pattern Recognition problem, the bigger the dataset, the better the system's performance.

However, in the signature verification context:

- The amount of data available for each user is often insufficient in real applications;
- During the enrollment phase, users are often required to supply only a few samples of their signatures;
- Acquisition and distribution of real signatures arise legal and privacy concerns;

The use of realistic synthetic signatures could be regarded as a good alternative.

The amount of samples used for training the signature verification system effects the system's performance. As any Pattern Recognition problem, the bigger the dataset, the better the system's performance.

However, in the signature verification context some points have to be considered:

The amount of data available for each user is often insufficient in real applications;

During the enrollment phase, users are often required to supply only a few samples of their signatures;

Acquisition and distribution of real signatures arise legal and privacy concerns;

Therefore, the use of realistic synthetic signatures could be regarded as a good alternative.

As a consequence, over the last years, several works on both online and offline signature synthesis have been carried out (Galbally Herrero et al., 2009; Galbally et al., 2012; Ferrer, Diaz-Cabrera, and Morales, 2013; Ferrer et al., 2013; Diaz-Cabrera et al., 2014).

If the synthetically generated signatures are similar to real ones, it might enable to enlarge existing datasets thus offering better recognition rates.

As a consequence, over the last years, several works on both online and offline signature synthesis have been carried out.

If the synthetically generated signatures are similar to real ones, it might enable to enlarge existing datasets to offer better recognition rates.

Online to Offline

Specifically, one possible synthethis apporach is the generation of synthetic offline signatures based on online samples.

ONLINE SIGNATURE (x_t, y_t, p_t) **-> OFFLINE SIGNATURE (2D image)**

Among others, this type of synthesis approach presents some practical applications:

- generation of synthetic static samples to be fused with the original online signatures in order to improve the performance in an online verification scenario;
- enlargement of existing offline signature datasets when complementary online data is available;
- development of systems capable of integrating both online and offline samples interchangeably, towards a unified signature biometry (Melo et al., 2017).

Specifically, one possible synthethis apporach is the generation of synthetic offline signatures based on online samples.
Among others, this type of synthesis approach presents some practical applications:

- creation of synthetic offline samples to be used as a complement to the original online signature to improve the recognition rate of an online verification system.
- enlarge existing offline signature datasets when complementar online data is available
- it can be used to create a unified signature representation, torward a system that can verify both online and offline samples

Goal

The goal of this work is to design an approach to generate synthetic offline handwriting signatures based on online data. This problem is modeled as a supervised machine learning task, through a Deep Convolutional Neural Network. This approach is evaluated in the context of enlargement of offline signature datasets to improve the offline signature verification systems performance.

"The goal of this work is to design an approach to generate synthetic offline handwriting signatures based on online data.

IN CONTRAST TO THE STATE-OF-THE-ART

We approach this problem as a supervised machine learning task, through a Deep Convolutional Neural Network.

Our proposed model is trained to learn the task “online to offline conversion”

This approach is evaluated in the context of enlargement of offline signature datasets to improve the offline signature verification systems performance.

Specific Goals

This statement is developed through the following actions:

- Creation and training of a Deep Neural Network model able to translate dynamic handwritten information into an offline manuscript;
- Generation of an offline synthetic dataset based on a publicly available online signature dataset
- Comparison of the proposed approach's performance with a state-of-the-art method to evaluate the closeness of synthetic signatures with respect to real signatures.

We design and train a Deep Neural Network model to **TRANSLATE** DYNAMIC HANWRITTEN INFORMATION to an STATIC IMAGE.

We apply our proposed methhod on a publicly available online signature dataset. We generate an offline synthetic dataset.

We evaluate the proposed synthetis approach with respect to real signatures and the state-of-the-art.

Contents

- Off-line Signature Synthesis Using On-line Samples
- Neural Networks and Deep Learning
- Proposed Method
- Evaluation Setup
- Results
- Conclusion and Future Works

From this introduction, the remainder of this presentation is structured as follows:

First we will give a brief description of the state-of-the-art method

Then we will give a brief overview of the Neural Networks and Deep Learning field, specifically the architecture we used in our proposed method.

Then, we describe our proposed method

Next, we describe the evaluation setup used to measure our proposed method performance

Then we present the results and finally the conclusion and suggestions for future works

Off-line Signature Synthesis Using On-line Samples

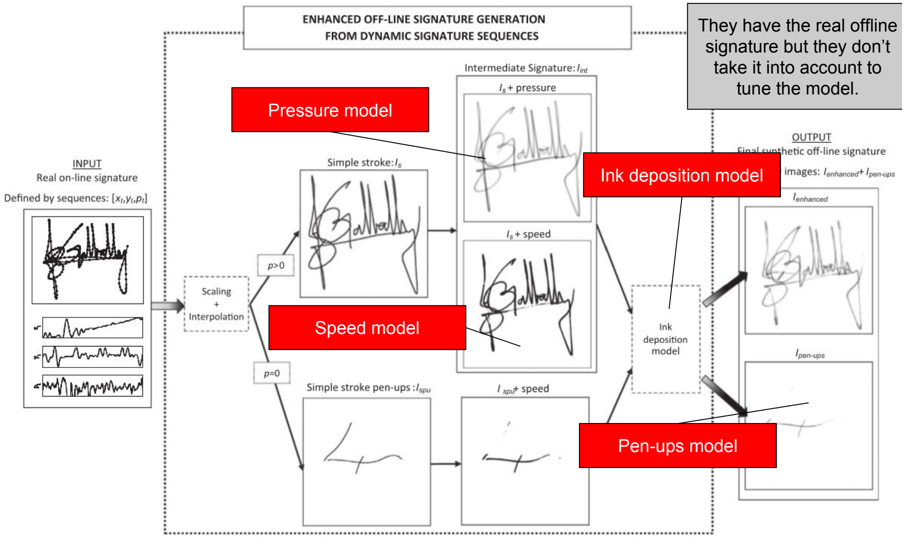


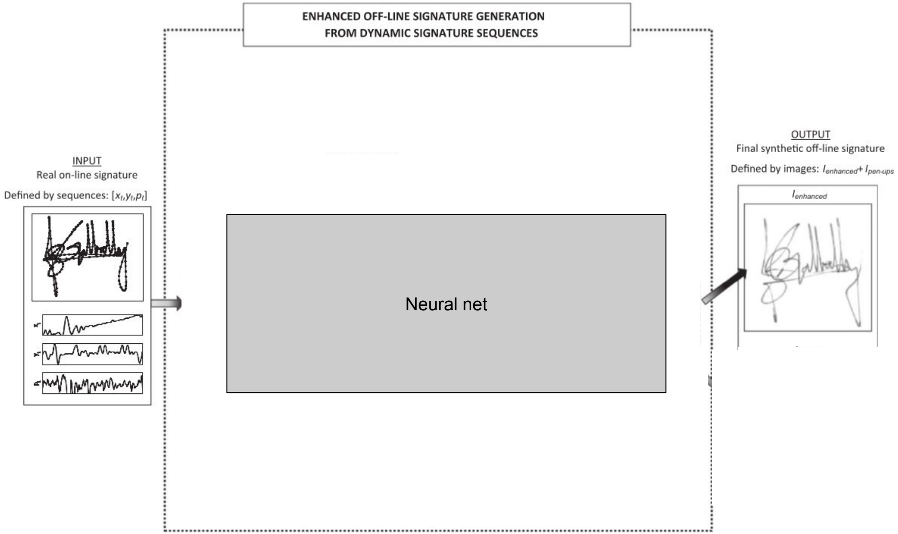
Figure 7: Method proposed by Diaz-Cabrera et al., 2014

This method was proposed by Diaz, they model **on to off conversion** as a 2D Gaussian function used to convert both pressure and velocity information to create the synthetic sample.

They also use, what refer to an ink-deposition model to estimate how these informations are translted to ink on a paper.

The generated signaures have close performance to the real signatures, but when used to increase the training dataset of a system, those samples struggle to improve the recognition rates.

Off-line Signature Synthesis Using On-line Samples



In contrast to what they proposed, instead of modeling this problem as some specific function, we make the neural network learn how this conversion is made, learning from data.

Neural Networks

- The Biological Neural Network is an essential part of the human brain.
- The human brain is a complex, non-linear and parallel "computer" consisting of **millions of connected neurons** (Haykin et al., 2009).
- It was observed that the mammal brain is organized in deep neural networks. The brain seems to process information though multiple stages (hierarchies).
- The depth of the neural network is characterized by the multiple levels of non-linear operations contained in the net.

The Biological Neural Network is an essential part of the human brain.

The human brain is a complex, **non-linear and parallel "computer"** composed of **millions of connected neurons**.

It was observed that the mammal brain is organized in deep neural networks. The brain seems to process information though multiple stages, or layers.

The depth of the neural network is characterized by the multiple levels of non-linear operations contained in the net.

Convolutional Neural Networks (CNN)

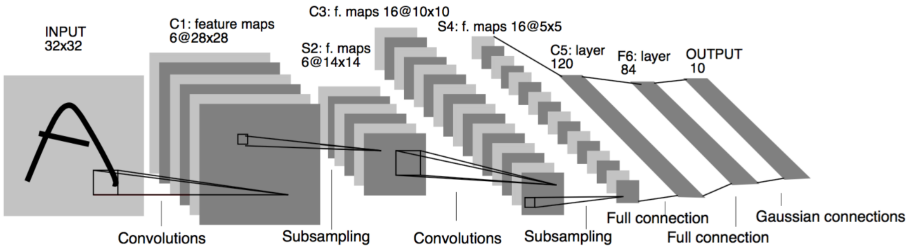


Figure 8: Lenet (LeCun et al., 1998)[4], a convolutional neural network used for handwriting recognition.

[4] Yann LeCun et al. (1998). "Gradient-based learning applied to document recognition". In: *Proceedings of the IEEE* 86.11, pp. 2278–2324.

One of the most succesful applications of deep learning is the convolutional neural network. The CNN is composed of several layers of trainable filters (convolutional layers) and sub-sampling operations, stacked in an alternating sequence starting from the input image.

Fully Convolutional Networks (FCN)

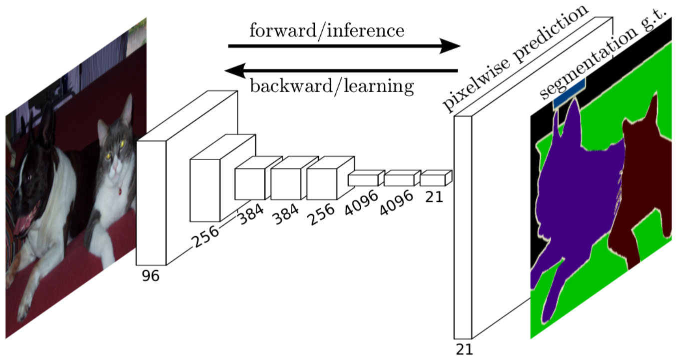


Figure 9: Fully convolutional networks can efficiently learn to make dense predictions for per-pixel tasks. Extracted from (Long, Shelhamer, and Darrell, 2015)[5]

[5] Jonathan Long, Evan Shelhamer, and Trevor Darrell (2015). "Fully convolutional networks for semantic segmentation". In: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 3431–3440.

The FCN, is a CNN modified for dense predictions While CNNs are typically built in a sequence of convolutional, subsampling, and fully connected layers.

The FCN adds an **expanding path** built with a **transposed convolutional layer** to recover spatial information.

Unlike a common CNN, which learns a general, nonlinear function that characterizes the input The FCNs **learn an end-to-end nonlinear mapping** from one input image to another.

It is kind of a pixel-wise prediction, where the label space is also transformed from a scalar unit to a two-dimensional image.

Outline of the Proposed Method

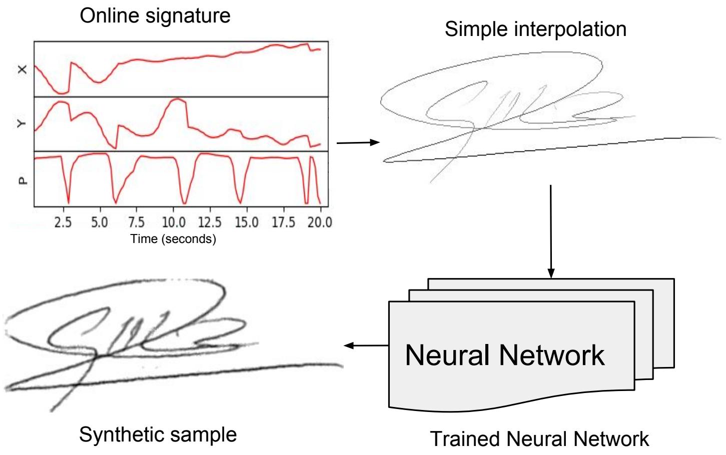


Figure 10: The proposed approach diagram and an example of the synthetic signature generation.

In this image, we can see an outline of how the proposed method works. The input online signature is interpolated to form an 2d Image to be used as input to the trained neural network and producing a synthetic offline signatures, as we can see int the picture.

Training Data

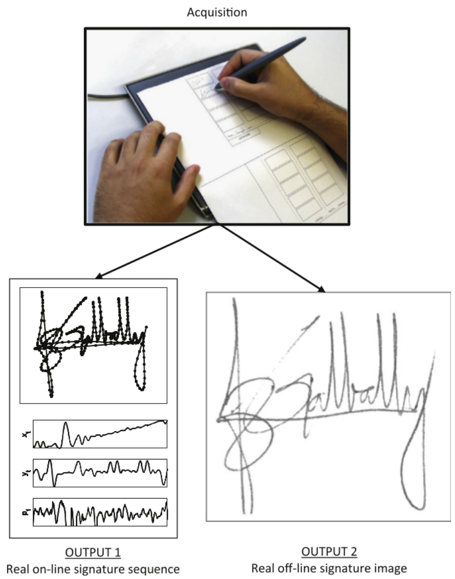


Figure 11: Figure extracted from (Galbally et al., 2015)

In order to acquire the online signature as well as the digital image for the same handwriting signal, some points have to be considered.

To acquire the data a form must be placed over a digitizng tablet to be filled with an electronic ink-pen. Then, the dynamic data is captured through the tablet, and the paper form can be scanned to provide the static data.

Thereby, two complementary files are available. One contains the dynamic information, and the other digital image.

Training Data

- We need both the online version of the manuscript mapped to the respective resulting offline representation.
- Dual modal signature datasets (BiosecurID, Biomet, MyIdea, Sigcomp2009, Sigma, SigwiComp2013, SigWiComp2015) had not this characteristic satisfied.
- Although acquired at the same time, both representations of the signatures do not match if we plot it in a single image.

Figure 12: A sample from the BiosecurID dataset. Here we can see that the online signature (interpolated in red) can not be projected on the respective offline version.

In order to train our model, we need both the online version of the manuscript mapped to the respective resulting offline representation.

The publicly available dual modal signature datasets had not this characteristic satisfied.

Although acquired at the same time, when we try to map it, both representations of the signatures do not match

As we can see, for instance, in this sample of the BiosecurID dataset. We can notice that the interpolated online signature can not be projected on the respective offline version.

Training Data

For this reason, we used the IRONOFF handwritting dataset to train our model. The IRONOFF dataset contains a total **of 23000 mapped online and offline manuscript samples**.

Figure 13: An offline manuscript mapped with the respective online trajectory. Image extracted from Viard-Gaudin et al., 1999.

Using this dataset, we make the fair assumption that if the neural network can perform the conversion on handwriting text, it would also work on handwritten signatures.

For this reason, we used the IRONOFF handwritting dataset to train our model. The IRONOFF dataset contains a total **of twenty three thousand mapped online and offline manuscript samples**.

In this image, we can see an interpolated handwriting sample mapped on the respective static image.

Using this dataset, we make the fair assumption that if the neural network can perform the conversion on handwriting text, it would also work on handwritten signatures.

Preprocessing

- Interpolate the online manuscript using the Bresenham algorithm, each pixel has the pressure information;
- Resize the samples to 383x150 pixels (maintaining the aspect ratio);
- Invert the pixels (so that the background corresponds to pixel intensity 0);
- Normalize the input according to the standard deviation of all pixel intensities.

(a) online input

(b) offline ground truth

During the training of our FCN model, two 2D matrices are needed. The online input and the offline target.

In order to craete a 2D representation of the online sample, we interpolate the online manuscript using the Bresenham algorithm, where each pixel is the pressure information

We resize the samples to a fixed size, using an appraoch to maintain the aspect ratio

we also invert the pixels, so that background is represented by the pixel intesity 0 and we normalize the data according to the standard deviation of all pixel intesities

Neural Network Model

The FCN was adopted to learn an end-to-end mapping from the online representation to the static image.

Table 1: The architecutre is a simplified version of the FCN-VGG (Long, Shelhamer, and Darrell, 2015; Simonyan and Zisserman, 2014)

Layer	Size
Convolution	16x3x3
Convolution	32x3x3
Convolution	32x3x3
Convolution	64x3x3
Transposed Convolution	64x3x3
Transposed Convolution	32x3x3
Transposed Convolution	32x3x3
Transposed Convolution	16x3x3

The FCN was adopted to learn an end-to-end mapping from the online representation to the static image

In this table, we can see the convlutional operations of the model architecture, this neural network architecture is a simplified version of the FCN-VGG.

Specific Details of the Neural Network

Some specific details of the Neural Network:

- Leaky Rectified Linear Units (LReLUs) were used as the activation function of all convolutional layers;

Leaky Rectified Linear Units were used as the activation function of all convolutional layers; **NEXT**

The ADAM optimizer was used (default parameters) to minimize the Mean Squared Error (MSE) for a hundred epochs; **NEXT**

The learning rate was set to dot o o one; **NEXT**

Mini-batches of size sixteen; **NEXT**

The weights were initialized using the method proposed by Glorot and Bengio, 2010; **NEXT**

twenty two thousand samples were used for training and a thousand for validation; **NEXT**

The network was trained using the library Tensorflow and it took around five days to train on a GTX six hundred seventy GPU.

Specific Details of the Neural Network

Some specific details of the Neural Network:

- Leaky Rectified Linear Units (LReLUs) were used as the activation function of all convolutional layers;
- The ADAM optimizer was used (default parameters) to minimize the Mean Squared Error (MSE) for 100 epochs;

Leaky Rectified Linear Units were used as the activation function of all convolutional layers; **NEXT**

The ADAM optimizer was used (default parameters) to minimize the Mean Squared Error (MSE) for a hundred epochs; **NEXT**

The learning rate was set to dot o o one; **NEXT**

Mini-batches of size sixteen; **NEXT**

The weights were initialized using the method proposed by Glorot and Bengio, 2010; **NEXT**

twenty two thousand samples were used for training and a thousand for validation; **NEXT**

The network was trained using the library Tensorflow and it took around five days to train on a GTX six hundred seventy GPU.

Specific Details of the Neural Network

Some specific details of the Neural Network:

- Leaky Rectified Linear Units (LReLUs) were used as the activation function of all convolutional layers;
- The ADAM optimizer was used (default parameters) to minimize the Mean Squared Error (MSE) for 100 epochs;
- The learning rate was set to 0.001;

Leaky Rectified Linear Units were used as the activation function of all convolutional layers; **NEXT**

The ADAM optimizer was used (default parameters) to minimize the Mean Squared Error (MSE) for a hundred epochs; **NEXT**

The learning rate was set to dot o o one; **NEXT**

Mini-batches of size sixteen; **NEXT**

The weights were initialized using the method proposed by Glorot and Bengio, 2010; **NEXT**

twenty two thousand samples were used for training and a thousand for validation; **NEXT**

The network was trained using the library Tensorflow and it took around five days to train on a GTX six hundred seventy GPU.

Specific Details of the Neural Network

Some specific details of the Neural Network:

- Leaky Rectified Linear Units (LReLUs) were used as the activation function of all convolutional layers;
- The ADAM optimizer was used (default parameters) to minimize the Mean Squared Error (MSE) for 100 epochs;
- The learning rate was set to 0.001;
- Mini-batches of size 16;

Leaky Rectified Linear Units were used as the activation function of all convolutional layers; **NEXT**

The ADAM optimizer was used (default parameters) to minimize the Mean Squared Error (MSE) for a hundred epochs; **NEXT**

The learning rate was set to dot o o one; **NEXT**

Mini-batches of size sixteen; **NEXT**

The weights were initialized using the method proposed by Glorot and Bengio, 2010; **NEXT**

twenty two thousand samples were used for training and a thousand for validation; **NEXT**

The network was trained using the library Tensorflow and it took around five days to train on a GTX six hundred seventy GPU.

Specific Details of the Neural Network

Some specific details of the Neural Network:

- Leaky Rectified Linear Units (LReLUs) were used as the activation function of all convolutional layers;
- The ADAM optimizer was used (default parameters) to minimize the Mean Squared Error (MSE) for 100 epochs;
- The learning rate was set to 0.001;
- Mini-batches of size 16;
- The weights were initialized using the method proposed by Glorot and Bengio, 2010;

Leaky Rectified Linear Units were used as the activation function of all convolutional layers; **NEXT**

The ADAM optimizer was used (default parameters) to minimize the Mean Squared Error (MSE) for a hundred epochs; **NEXT**

The learning rate was set to dot o o one; **NEXT**

Mini-batches of size sixteen; **NEXT**

The weights were initialized using the method proposed by Glorot and Bengio, 2010; **NEXT**

twenty two thousand samples were used for training and a thousand for validation; **NEXT**

The network was trained using the library Tensorflow and it took around five days to train on a GTX six hundred seventy GPU.

Specific Details of the Neural Network

Some specific details of the Neural Network:

- Leaky Rectified Linear Units (LReLUs) were used as the activation function of all convolutional layers;
- The ADAM optimizer was used (default parameters) to minimize the Mean Squared Error (MSE) for 100 epochs;
- The learning rate was set to 0.001;
- Mini-batches of size 16;
- The weights were initialized using the method proposed by Glorot and Bengio, 2010;
- 22000 samples were used for training and 1000 for validation;

Leaky Rectified Linear Units were used as the activation function of all convolutional layers; **NEXT**

The ADAM optimizer was used (default parameters) to minimize the Mean Squared Error (MSE) for a hundred epochs; **NEXT**

The learning rate was set to dot o o one; **NEXT**

Mini-batches of size sixteen; **NEXT**

The weights were initialized using the method proposed by Glorot and Bengio, 2010; **NEXT**

twenty two thousand samples were used for training and a thousand for validation; **NEXT**

The network was trained using the library Tensorflow and it took around five days to train on a GTX six hundred seventy GPU.

Specific Details of the Neural Network

Some specific details of the Neural Network:

- Leaky Rectified Linear Units (LReLUs) were used as the activation function of all convolutional layers;
- The ADAM optimizer was used (default parameters) to minimize the Mean Squared Error (MSE) for 100 epochs;
- The learning rate was set to 0.001;
- Mini-batches of size 16;
- The weights were initialized using the method proposed by Glorot and Bengio, 2010;
- 22000 samples were used for training and 1000 for validation;
- The network was trained using the library Tensorflow and it took around five days to train on a GTX 670 GPU.

Leaky Rectified Linear Units were used as the activation function of all convolutional layers; **NEXT**

The ADAM optimizer was used (default parameters) to minimize the Mean Squared Error (MSE) for a hundred epochs; **NEXT**

The learning rate was set to dot o o one; **NEXT**

Mini-batches of size sixteen; **NEXT**

The weights were initialized using the method proposed by Glorot and Bengio, 2010; **NEXT**

twenty two thousand samples were used for training and a thousand for validation; **NEXT**

The network was trained using the library Tensorflow and it took around five days to train on a GTX six hundred seventy GPU.

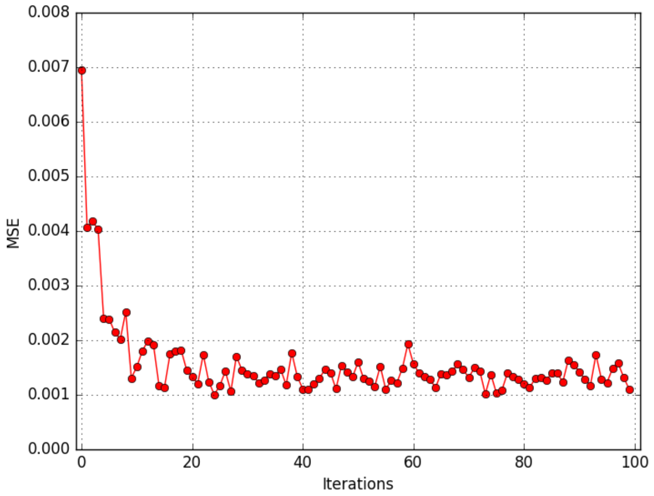


Figure 14: Validation loss versus the iterations.

This is the loss over the iteration graph, we can see that the loss was varying from dot o o two to dot o o one, from iteration twenty until the last iteration.

Training results

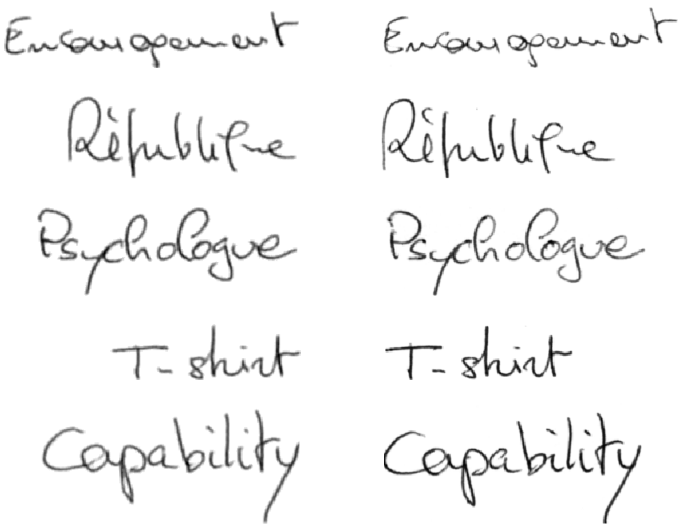


Figure 15: A not cherry-picked selection of synthetic manuscripts produced using our proposed method (left) alongside the expected output (right).

In this picture we can see the sytnhetic samples created with the network, it is somewhat close to the expected output, but in order to have an objective evalution of the quality of the samples in the context of signature verification we performed a machine-oriented evalution.

Evaluation Setup

To evaluate the quality of the synthetic signatures

- We use a state-of-the-art offline signature verification system;
- We use a dataset containing both online and offline signatures.

The synthesis quality is measured by the offline verification system performance. **The questions raised are:**

- is the synthetic signatures system performance similar to the offered by real offline signatures?
- is it feasible to increase the number of samples at the enrollment phase with the synthetic signatures generated with our proposed method?

To evaluate the quality of the synthetic signatures

We use a state-of-the-art offline signature verification system;

We use a dataset containing both online and offline signatures.

The synthesis quality is measured by the offline verification system performance. **The questions raised are:**

is the synthetic signatures system performance similar to the offered by real offline signatures?

is it feasible to increase the number of samples at the enrollment phase with the synthetic signatures generated with our proposed method?

Offline signature verification system

Offline handwritten signature verification system:

- The features were extracted using the approach proposed by Hafemann, Sabourin, and Oliveira, 2017[6]. This approach uses ideas from transfer learning and multi-task learning to learn features using a Convolutional Neural Network (CNN).
- The classifier is a Linear SVM

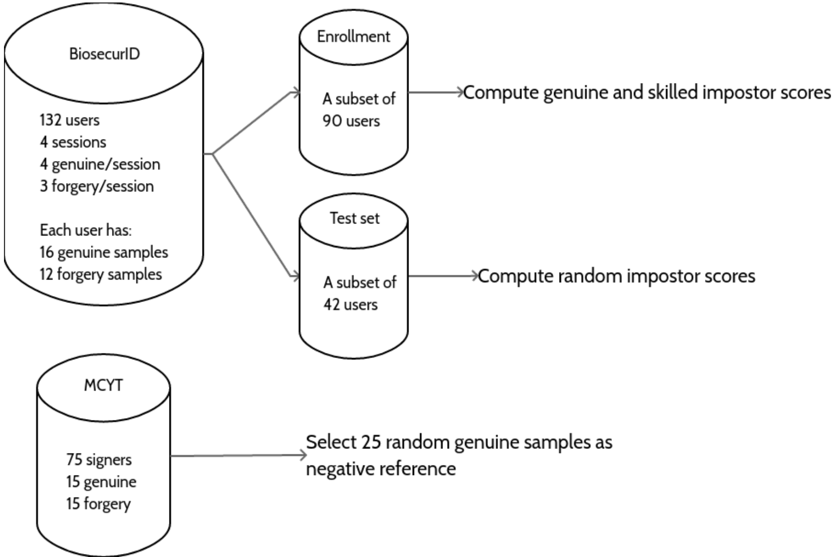
[6] Luiz G Hafemann, Robert Sabourin, and Luiz S Oliveira (2017). "Learning features for offline handwritten signature verification using deep convolutional neural networks". In: *Pattern Recognition* 70, pp. 163–176.

The system used for the evaluation of the real and synthetic signatures is a Linear SVM classifier and with a state-of-the-art feature extraction approach, proposed by Hafeman, Sabouran and Oliveira.

The feature extraction system uses ideas from transfer learning and multi-task learning, in the context of offline signature verification, to learn features using a Convolutional Neural Networks (CNN).

Database

The evaluation experiments were carried out on the BiosecurID database (Fierrez et al., 2010).



It is an online and offline database publicly available containing signatures of **one hundred thirty two** subjects. Both versions, online and offline, of the same real signature were acquired at the same time.

The signatures samples were captured in four different sessions, distributed over four months. Each subject signed four times and forged threesignatures per session.

Therefore, Each subject has sixteen genuine samples and twelve skilled forgeries.

For all experiments we splited the dataset as enrollment and test. The first ninety users are used for enrollment and the last forty two are used as the testing set.

in the training phase the verification system requires negative samples, we used the MCYT database as the negative dataset samples.
We selected twenty five random samples from the MCYT dataset to use as negative reference for each user.

Experiments

We follow the same experiment protocol proposed by Diaz-Cabrera et al., 2014. Two different experiments are carried out.

- Experiment 1 focus on evaluating the synthetic signatures performance in comparison to real signatures
- Experiment 2 evaluates the feasibility of synthetically increasing the number of samples available in a dataset.

We follow the same evaluation protocol followed by Diaz: Two different experiments: Experiment 1 compares the synthetic signatures performance in comparison to real signatures

Experiment 2 evaluates the feasibility of increasing the enrollment dataset using synethci samples.

Experiment 1

We evaluate the offline signature verification system performance using only synthetic samples and using only real samples their recognition rates.

Each user model is trained with:

- 4 genuine signatures
- 25 random samples from MCYT

The score is measured with:

- For each user the remaining 12 genuine samples are used to measure the genuine score. 90x12 = 1080 genuine scores
- Random impostor scores are calculated comparing the first sample of each test subject to the enrolled model, leading to 90x42 = 3780 random impostor scores.
- The skilled impostor scores are calculated with the skilled forgeries samples of the enrolled users (12 per subject), leading to 90x12 = 1080 skilled impostor scores.

We evaluate the offline signature verification system performance using only synthetic samples and using only real samples their recognition rates.

For each user, we train a model using four genuine signatures and twenty five random samples from MCYT

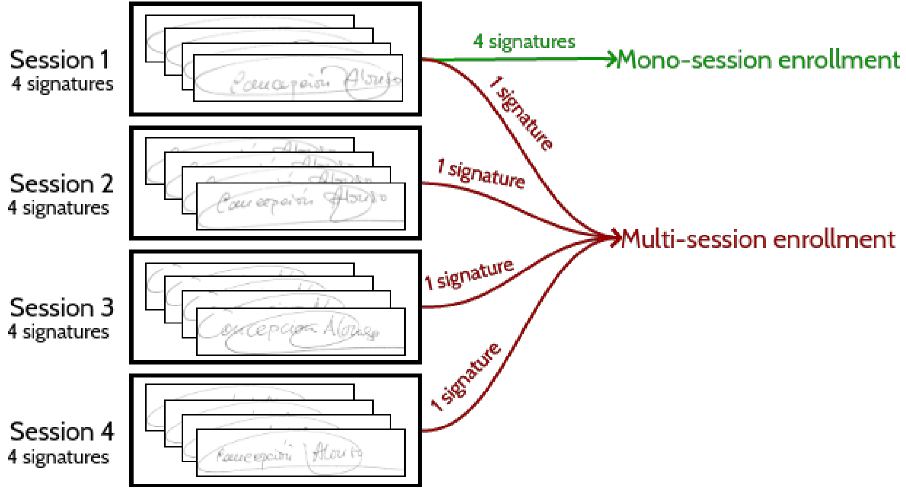
The genuine score is obtained the remaining genuine samples

The skileld forgery score is obtained with all skilled forgeries samples of the user

And the random forgery score is obtained using 42 signatures from the test set.

Experiment 1

Two different protocols have been considered to compute the 90 users models: a **mono-session** approach and a **multi-session** approach.



Two enrollment phases are evaluated

The difference is the genuine reference used for training the model

In the mono-session enrollment, all the four signatures of the first session is used

In the multi-session, one sample of each session is used to create the genuine reference set

Experiment 2

Experiment 2 is designed to assess whether **synthetically increasing the enrollment dataset leads to a better recognition performance**. Three different enrollment sets are considered in this experiment:

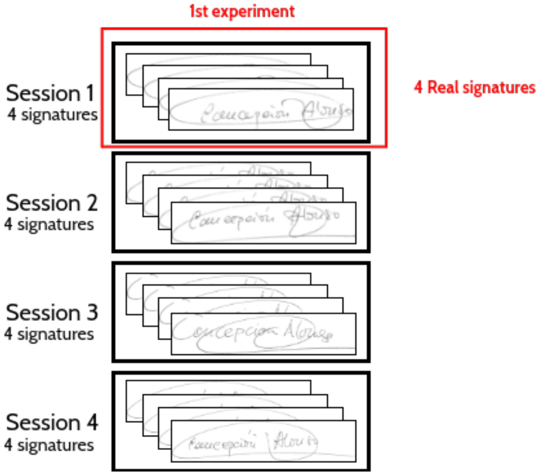
- 4 real samples belonging to the first acquisition session
- 8 real samples belonging to the first and the second sessions
- 4 real samples belonging to the first session plus 4 synthetic samples belonging to the second session.

Experiment 2 is designed to assess if the synthetic signatures can be used to increase the training dataset to improve the recognition rates.

Three different enrollment sets are considered

Experiment 2 - First Enrollment

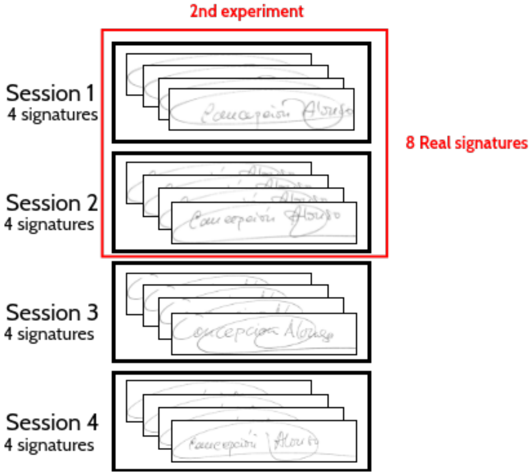
4 real samples belonging to the first acquisition session



The first enrollment set is built with 4 real sigantures, as we can see in the picture

Experiment 2 - Second Enrollment

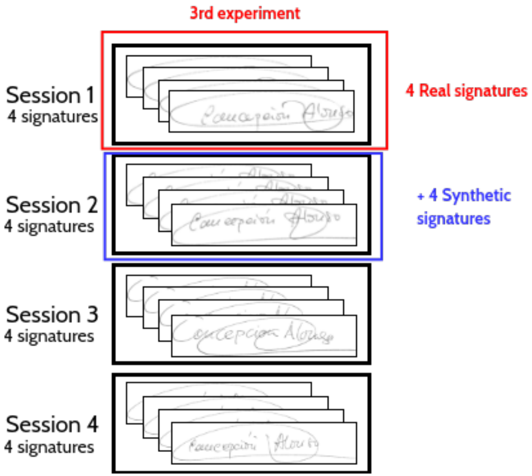
8 real samples belonging to the first and the second sessions



The second enrollment set is built with eight real signatures from session one and session 2, we expect that the system’s performance improves with this enrollment approach.

Experiment 2 - Third Enrollment

4 real samples belonging to the first session plus 4 synthetic samples belonging to the second session.



The third enrollment set, uses four real signatures from the first session and four synthetic signatures from the second session.
Given that using eight real signatures is better than using only 4 real signatures, we expect a similar result to using eight real signatures.

Performance Assessment

The performance is measured as the efficiency of the signature verification system.
The system is quantitatively measured by two rates:

- False Rejection Rate (FRR): genuine samples classified as forgeries;
- False Acceptance Rate (FAR): forgeries classified as genuine.

When experimenting on signature verification systems, the trade-off between FRR and FAR must be taken into account. When the **decision threshold is set to have the FRR equal to the FAR, the Equal Error Rate (EER)** is calculated. In our experiments the EER is reported.

The performance is measured as the efficiency of the signature verification system.

The system is quantitatively measured by two rates: False Rejection Rate and False Acceptance Rate

When the **decision threshold is set to have the FRR equal to the FAR, the Equal Error Rate (EER)** is calculated. In our experiments the EER is reported.

Results

The goal of the experiments are:

- Measure the quality of the synthetic images;
- Assess whether using synthetic signatures effects the recognition performance of an offline signature verification system; and
- Analyze the feasibility of using real and synthetic signatures on the enrollment set.

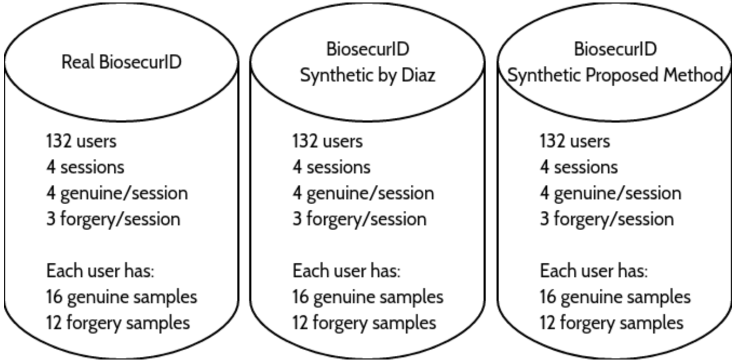
We compare our results with the state-of-the-art method, the approach proposed by Diaz *et al.* **The reported EER is achieved for both approaches in the same experimental conditions.**

The goal of the experiments are to measure the quality of the synthetic samples, to assess whether synthetic signatures affects the recognition rates of an offline signature verification system and to analyze the feasibility of increasing the training dataset with synthetic samples

We compare our results with the approach proposed by Diaz. The reported EER is achieved for both approaches in the same experimental conditions.

Results

We report the results of three versions of the BiosecurID dataset:



Three types of signatures are mentioned

real offline signatures, which are the corresponding real offline samples, the ideal synthetic signature should be similar to it;

synthetic signatures generated with the method proposed by Diaz *et al.*

synthetic signatures created with our proposed method

Experiment 1

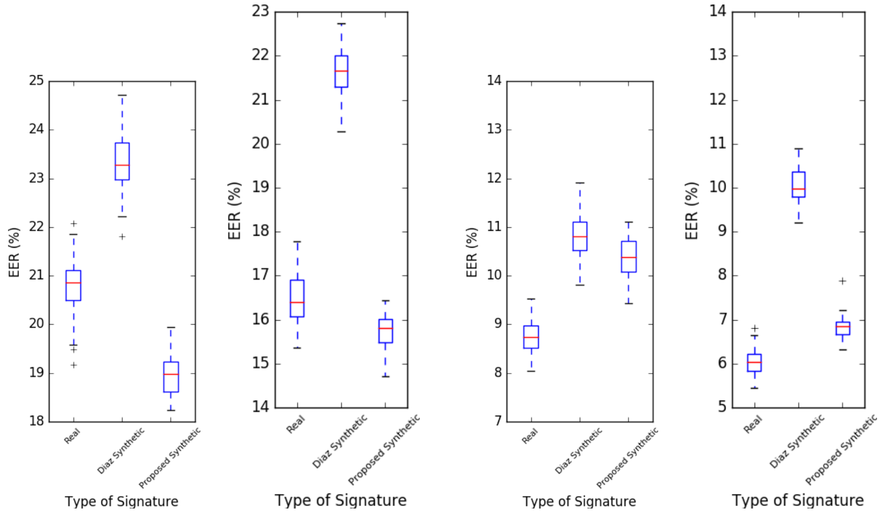
Table 2: EER for real, synthetic samples from Diaz *et al.* Diaz-Cabrera et al., 2014 and our proposed method synthetic offline signatures, for all the approaches considered under the two possible scenarios (i.e., random and skilled forgeries)

Mode	**Skilled Forgeries**		
	Real	**Diaz *et al.***	**Proposed method**
mono-session	20.28%	23.19%	18.38%
multi-session	17.59%	22.27%	16.48%
	Random Forgeries		
	Real	**Diaz *et al.***	**Proposed method**
mono-session	9.07%	10.65%	9.99%
multi-session	5.60%	10.00%	6.48%

In this table we can see that under the skilled forgeries scenario, our proposed method synthetic signatures yields better recognition rates than both real offline signatures and the state of the art method

On the random forgeries test we can see that the recognition rates obtained by the real and both types of synthetic samples are close to each other.

Experiment 1 - running 30 times



(a) mono-session - skilled forgeries (b) multi-session - skilled forgeries (c) mono-session - random forgeries (d) multi-session - random forgeries

Figure 16: Boxplot comparison for running 30 times the Experiment 1

We can see that when running the experiments 30 times, the results are consistent with a low dispersion around the mean.

We can notice that our proposed method is able to generate synthetic signatures comparable to real signatures.

Experiment 2

Table 3: EER for real, synthetic samples from Diaz *et al.* Diaz-Cabrera et al., 2014 and our proposed method synthetic offline signatures for the Experiment 2 under the two possible scenarios, i.e., random (RF) and skilled forgeries (SF)

Genuine Training	SF	RF
4 real samples	21.55%	10.26%
4 real + 4 real samples	19.72%	7.63%
4 real + 4 synthetic from Diaz *et al.*	24.19%	7.72%
4 real + 4 synthetic from the Proposed Method	19.17%	9.74%

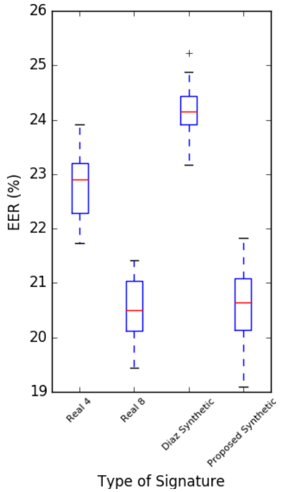
In the first line, we can observe the recognition rates obtained using only 4 real samples.

Below it, it is reported the recognition rates using 8 real signatures, and 4 real signatures plus the synthetic signatures created with the method proposed by diaz and our proposed method.

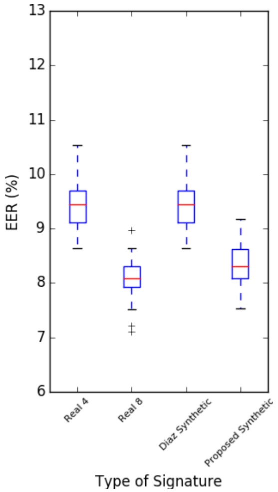
Specifically, our proposed method yields a improved recognition rate on the skilled forgery scenario

In the random forgery scenario the improvement is not as good as using real signatures, but the recognition rate is better than using only four signatures.

Experiment 2 - running 30 times



(a) mixed enrollment - skilled forgeries



(b) mixed enrollment - random forgeries

When running the experiments thirty times, we can notice that the results have a consistent result around the mean. It is possible for us to conclude that it is possible to user our proposed system to generate synthetic signatures to increase the enrollment dataset and improve the recognition rate of offlien signature verification systems.

Conclusion

- A Fully Convolutional Neural Network was proposed to learn an end-to-end mapping from the online to the offline domain;
- We show that it is possible to model the "online to offline signature conversion" as a learning from data task.
- We observe that the synthetic offline signatures generated with the proposed method offer a verification performance similar to the one offered by real signatures
- We show that the synthetic signatures present high discriminative power when used to increase the enrollment set under the skilled forgeries scenario.

A Fully Convolutional Neural Network was proposed to learn an end-to-end mapping from the online to the offline domain; We show that it is possible to model the "online to offline signature conversion" as a learning from data task.

We observe that the synthetic offline signatures generated with the proposed method offer a verification performance similar to the one offered by real signatures

We show that the synthetic signatures present high discriminative power when used to increase the enrollment set under the skilled forgeries scenario.

Future Works

- Explore the optimization of the hyper-parameters of the FCN (such as the number of layers, number of neurons per layer, different architectures)
- Integrate other dynamic features in addition to the pressure on the input of the neural network, such as the velocity.
- Design a model to synthesize offline signatures with bigger resolution.
- Combine real online and synthetically generated offline signatures using the proposed method, when only the online information is available, towards improved recognition results on a dynamic signature verifier.

Explore the optimization of the hyper-parameters of the FCN (such as the number of layers, number of neurons per layer, different architectures)

Integrate other dynamic features in addition to the pressure on the input of the neural network, such as the velocity.

Design a model to synthesize offline signatures with bigger resolution.

Combine real online and synthetically generated offline signatures using the proposed method, when only the online information is available, towards improved recognition results on a dynamic signature verifier.

Universidade de Pernambuco - UPE
Escola Politécnica de Pernambuco - POLI
Mestrado em Engenharia da Computação

A Deep Learning Approach to Generate Offline Handwritten Signatures Based on Online Samples

Victor Kléber Santos Leite Melo
vkslm@ecomp.poli.br

Advisor: Prof. Dr. Byron Leite Dantas Bezerra
Co-Advisor: Prof. Dr. Giuseppe Pirlo

August 28, 2017

ty