Offline Signature Biometrics using Siamese Neural Networks

Varad V Pathak, Manjunath Hiremath, Joy Paulose

MSc Scholar, Christ (Deemed to be University
Assistant Professor, Christ (Deemed to be University)
Professor, Christ (Deemed to be University)

Abstract

The evolution of technology has made certain things easier for people, like keeping the confidentiality of information in check. On similar lines, Biometric systems have also evolved from having a single finger print to retinal biometrics. Biometric Systems have helped in verifying many of such human traits like signature, face, gait, fingerprint. Although, many modern systems have been introduced yet signatures have remained prevalent in successfully authorizing official documents and verifying individuals. Many models have been proposed – using PCA, LDA, Neural Networks, and SVM to verify such offline and online signatures. This paper aims to compare many of such models and proposes another on the basis of the survey made with a primary implementation of the same that would take less data to train the model and yet provide with an average to optimum result.

Keywords: Biometrics, Fingerprint, Siamese Neural Networks, Contrastive Loss Function, One shot learning, Verification.

2010 MSC: 00-01,99-00

1. Introduction

The evolution of Biometric systems has helped us with the recognition and verification of uniquely human traits. Bio-metric that literally means life and measure deal with automatically authenticating people based on their physiological and behavioural characteristics. Wherein Fingerprint, Iris, Face, Voice come under physiological whereas gait, signature and keystrokes are behavioural traits. To elucidate, Physiological are based on measurements of parts of the body, one which is not expected to change throughout a man's life. On the other hand, behavioural traits are ones that are determined by the manner of doing a particular task. These are often affected by external factors such as physical or emotional health. Signature is one such behavioural trait that has been considered a valuable method of verification for decades. Modern-day technology has provided us with two major methods of Signature Verification – Offline Signature Verification and Online Signature Verification.

(a) Online signature **(b)** Offline signature

Figure 1: Comparison of online and offline signatures

As the name suggests, offline signature verification involves the process of taking scans of the handwritten signatures and then processing them for recognition, while the latter refers to taking signatures with the help of a tablet and an e-pen.

Clearly, the two methods have different techniques for identification of features like time delay or minute calligraphical features although online verification system usually requires some capital investment and therefore for regions where people are still paper-bound, offline signature verification system has an edge over the former.

2. Literature Survey

Researchers have produced prolific results from their experiments in attempts to yield maximum accuracy in verifying the signatures. Using geometrical and statistical approaches along with traditional algorithms has consistently proved helpful for researches.

A paper on Biometric modalities [1] explained various techniques that can be used for verification wherein feature based methods were preferred thereby producing results that were resistant to forgery including non-intrusiveness but were prone to signature inconsistencies and its difficulty to use it.

Another paper [8] discussed verification by combining Zernike moments with Radon transform values at a different angle of projection from the user's Signature pattern and then forming a statistical state machine with HMM and PLSR. The pre-processing included – Grayscale conversion, converting to Binary, Simple Bounding Box, Binarization of the image in the background and foreground. The model tends to improve using kernel-based techniques with the Help of SVM. Although, when it comes to detecting discontinuous signatures as presented in the proposed system it failed to verify because it is assumed that the image is at the center of the box.

A paper on signature verification using PCA and geometrical features [9] took signature inputs individually from different people. As part of preprocessing RGB was converted to Grayscale for Pre-processing (Noise Removal – Median Filter Method). Geometrical approaches were taken into consideration to describe local descriptors. The Direction of signature was determined using PCA by computing angle for each signature block and similarly, the Sobel edge map was obtained. Although the outcomes of the experiment resulted in 97.6 % accuracy and 2.6% rejection rate, the same cannot be said for forged test set where the result for acceptance is 96.0 % and rejection 4.0%.

One of the papers discussed a method involving Walsh Coefficient of Pixel Distribution, Codeword Histogram based on clustering technique (vector quantization), Special moments of codewords, grid and texture features and successive geometric centers of depth [2]. The practical/physiological parameters they used included- Tip of pen, Signatures taken at different times (Psychological or Emotional states), Aging, etc. and used several metrics and features comprising of decision thresholds required for classification are calculated by considering the variation of features among the training set, False Acceptance Ratio (FAR) and False Rejection Ratio (FRR), Number of pixels, Picture Width (in pixels), picture heights (in pixels), horizontal max projections, vertical max projections, dominant angle - normalized, baseline shift, tri-surface areas. Walsh Transform of the vertical and horizontal pixel projections, then vector. Quantization-based codeword histograms were used to extract features and use them as feature vectors. Grid, Texture features, and Successive Geometric Centers (depth = 2) were also extracted from the mentioned features. Test sets were divided for 1) Recognition and 2) Verification, with several metrics for signatures – forged, casual, skilled, genuine. The system, with a decision threshold of 60% achieved a final FAR as 2.5% and overall combined accuracy as 95.08%, and the EER as 3.29% for Recognition. While for verification, 93.08% accuracy and 6% EER.

A review paper [4] suggested a combination of Neural Network and SVM provided a good understanding of how the SVM and Neural Networks work in the biometric recognition and verification but does not provide an in-depth explanation of the methods (SVM or Neural Network) reviewed by the authors.

Demonstration of One-Shot Recognition of the Siamese Neural Network on steel surfaces [3] provided a two-fold contribution in the automation of quality control. Presented architecture is not optimum in this paper. But the given system comprised only single-channel image data of surface defects to inspect steel surfaces. Data from sensors capable of detecting more features could further enhance the system.

3. Model Proposed

3.1 Siamese Neural Networks

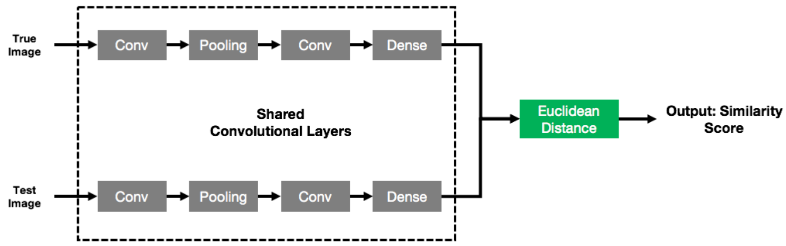


Figure 2: Architecture of a Siamese Neural Network

The process of learning good features could be computationally time taking with a huge training set, so there is a need to learn more features with less training data that could be tested on an entirely new distribution of test sets [10]. Using a convolutional architecture, we are able to achieve strong results which exceed those of other deep learning models with near state-of-the-art performance on one-shot classification tasks.

Deep Convolutional Neural Networks are such multilayer neural networks used for classification images in bulk [6]. These multi-layered neural networks are used with variable kernel sizes, pooling layers and fully connected layer that further classifies the images to its respective classes.

Siamese Neural Networks are a class of such Deep CNNs that contains two CNN with the same hyperparameters. The input image goes through several layers of convolution, activation and pooling, and then to the fully connected layer to give the 1-Dimensional tensor and after learning of the network, the output goes to a Loss function which compares the two output and computes the similarity/dissimilarity between them, based on the set threshold, the model verifies the image being tested as genuine or not. This framework has been successfully used for dimensionality reduction in weakly supervised metric learning and for face verification.

3.2 Architecture

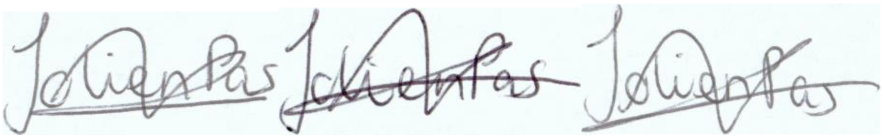
A variation of kernel sizes from 3 to 11 have been used. The parameters used in this architecture are as follows –

Layer	**Size**	Parameters
Convolution	96 × 11 × 11	$stride = 1$
Local Response Norm	-	$\alpha = 10{-}4, \beta = 0.75, k = 2, n = 5$
Pooling	96 × 3 × 3	$stride = 2$
Convolution	256 × 5 × 5	$stride = 1, pad = 2$
Local Response Norm	-	$\alpha = 10{-}4, \beta = 0.75, k = 2, n = 5$
Pooling + Dropout	256 × 3 × 3	$stride = 2, p = 0.3$
Convolution	384 × 3 × 3	$stride = 1, pad = 1$
Convolution	256 × 3 × 3	$stride = 1, pad = 1$
Pooling + Dropout	256 × 3 × 3	$stride = 2, p = 0.3$
Fully Connected + Dropout	1024	$p = 0.5$
Fully Connected	128	

Table 1. Overview of the constituting CNNs

3.3 Dataset

The dataset used for the current application is taken from ICDAR 2011 Signature Dataset. Signatures [7] are divided into two categories as skilled and forged. The dataset contains total of 5120 signatures collected from twenty different people. Each person has twelve genuine signatures and 12 forged signatures. A labelled spreadsheet is also provided for both training and testing the model. The model is trained on 20 epochs with a batch size of 32.



(a) Sample Original Signatures of individual

(b) Sample Forged Signatures of individual

Figure 3: Sample of Original and Forged classes signature under the given dataset

3.3 Loss Function

Contrastive loss measures the difference between a positive example and another example of the same class and compares it to the distance between negative examples.

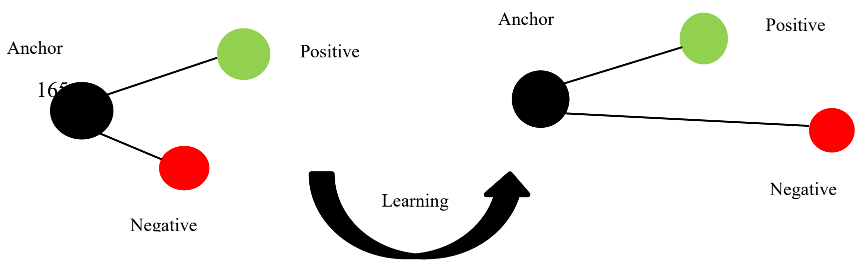


Figure 4: Contrastive Loss Function

To find out the similarity between the two input images a Contrastive Loss function [5] is used to calculated to distance based on Euclidean distance.

$$L(W, Y, X_1, X_2\,) = \left((1 - \mathrm{Y})\frac{{D_w}^2}{2} + Y\,\frac{\max(0,\;\; m - D_w)}{2} \right)$$

Where X_1, X_2 are input vectors and parameterized distance function to be learned D_W where $m > 0$. The margin m defines a radius around G_W (X), a parameterized function G_W, in such a way that neighbors are pulled together and non-neighbors are pushed apart. Dissimilar pairs contribute to the loss function only if their distance is within this radius. The term L_D, involving the contrastive pair is crucial.

RSMprop optimizer is used with learning rate $1e^{-4}$, alpha as 0.99, epsilon as $1e^{-8}$, *weight_decay* as 0.0005, momentum as 0.9 as suggested by the work of Handsell and Raja [5].

4. Observation

Figure 4: Dissimilarity scores between forged and original

The model was trained by the Siamese Neural Network, weights were generated and applied for evaluation upon the testing data. The model made predication for each of the individual inputs between the two categories Original and Forged using the dissimilarity score calculated by the Comparative Loss Function by the end of the two individual Convolutional Neural Networks. The predictions that were made for each of the twenty individual test sets, fifteen were correctly identified as per the dissimilarity score and given label while the remaining five were classified as false positives and false negatives. The classification report of the predictions made are provided in the figure below -

Test data - 20 samples		Predicted	
		Original	Forged
TRUE	Original	9	3
	Forged	2	6

Figure 5: Classification Report for the observed output

5. Conclusion

Thus, the given setting of the architecture and set of parameters gave us an average trained model that was trained using comparatively less data used for regular CNN models. The model was evaluated using test input data for twelve unknown signatures and yielded with the best possible solution with the given settings of layer and kernels. One of the future directions could be to find out better values of hyperparameters for the model. To improve the efficiency, we can make use of different loss functions like non-marginal loss function for Siamese Networks and compare the results with the Contrastive loss function. After getting suggestable sufficiently good results the model can be applied to a self-prepared dataset or the CEDAR dataset or and the model can be evaluated on the basis of the performance over them.

6. Acknowledgment

The authors are grateful to the referees for their helpful comments and suggestions. Also, the authors are indebted to the CHRIST (Deemed to be University), for the support for this research work under MRPDSC1827 grant.

7. References

[1] Goudelis, Georgios & Tefas, Anastasios & Pitas, Ioannis. (2009). Emerging biometric modalities: A survey. Journal on Multimodal User Interfaces. 2. 217-235. 10.1007/s12193-009-0020-x.

[2] Bharadi, Vinayak & Kekre, Hemant. (2010). Off-Line Signature Recognition Systems. International Journal of Computer Applications. 1. 10.5120/499-815.

[3] Deshpande, Aditya & Minai, Ali & Kumar, Manish. (2020). One-Shot Recognition of Manufacturing Defects in Steel Surfaces.

[4] Kaur, Rapanjot & Aujla, Gagangeet. (2014). Review on: Enhanced offline signature recognition using neural network and SVM. International Journal of Computer Science and Information Technologies", Volume5 (3).

[5] Hadsell, Raia & Chopra, Sumit & Lecun, Yann. (2006). Dimensionality Reduction by Learning an Invariant Mapping. 1735 - 1742. 10.1109/CVPR.2006.100.

[6] Bell, Sean & Bala, Kavita. (2015). Learning visual similarity for product design with convolutional neural networks. ACM Transactions on Graphics. 34. 98:1-98:10. 10.1145/2766959.

[7] Jagtap, Amruta & Sawat, Dattatray & Hegadi, Rajendra & Hegadi, Ravindra. (2020). Verification of genuine and forged offline signatures using Siamese Neural Network (SNN). Multimedia Tools and Applications. 10.1007/s11042-020-08857-y.

[8] A Simple Signature Recognition System, Suvarnsing G. Bhable, IOSR Journal of Mechanical and Civil Engineering (IOSR-JMCE) e-ISSN: 2278-1684,p-ISSN: 2320-334X, Volume 12, Issue 6 Ver. IV (Nov. - Dec. 2015), PP 79-82.

[9] Basavanna M, Prem Singh M, Chandraiah T, Prakash Raje Urs M, "Signature Verification using PCA and Geometric functions", Volume 9 Issue 3 - January 2018, 57-62.

[10] Gregory Koch, Richard Zemel & Ruslan Salakhutdinov, “Siamese Neural Networks for One-Shot Image Recognition.” (2015), ICML deep learning workshop, vol. 2. 2015.