Learning Metric Features for Writer-Independent Signature Verification using Dual Triplet Loss

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ICPR 2020
25th INTERNATIONAL CONFERENCE ON PATTERN RECOGNITION
Milan, Italy 10 | 15 January 2021

Introduction

Handwritten signature is one of the most common biometric features for verification in real life. Given a number of reference samples, a signature verification system should tell forgeries from genuine signatures even if the forger were given samples of the original writer.

genuine samples

skilled forgeries

Metric Learning (triplet loss)

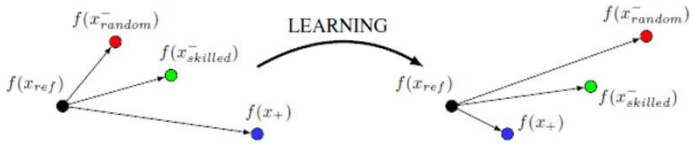
Metric Learning first transforms input batches into high dimensional feature embeddings. The Triplet Loss then minimizes the distance between an anchor and a positive, both of which have the same identity, and maximizes the distance between the anchor and a negative of a different identity.

In this case, the loss being minimised turn out to be:

$$\sum_{i}^{N}\left[\|f(x_i^a)-f(x_i^p)\|_2^2-\|f(x_i^a)-f(x_i^n)\|_2^2+\alpha\right]_+$$

where the embedding $f(\cdot)$ of an image x_i^a (anchor) of a specific person should be closer to all other images x_i^p (positive) of the same person than it is to any image x_i^n (negative) of any person, and α is a margin enforced between positive and negative pairs. [1]

Dual Triplet Loss



When training using dual triplet loss, we consider both the random forgeries and skilled forgeries. Random forgeries refer to signatures from other different users, and skilled forgeries are collected by forgers who imitate the original writing pattern of a specific user.

We want the embedding of genuine samples $f(x_+)$ closer to the reference sample $f(x_{ref})$ than forgeries, either random $f(x^-_{random})$ or skilled $f(x^-_{skilled})$. And $f(x^-_{skilled})$ should be intuitively farther from $f(x_{ref})$ than $f(x^-_{random})$

Two losses:

$$\mathcal{L}_{random} = \ln(1+\exp(\max_{x_+\in\mathcal{T}_{batch}}\|f(x_{ref})-f(x_+)\|_2^2 - \|\min_{x^-_{random}\in\mathcal{T}_{batch}} f(x_{ref})-f(x^-_{random})\|_2^2 + \alpha))$$

$$\mathcal{L}_{skilled} = \ln(1+\exp(\max_{x_+\in\mathcal{T}_{batch}}\|f(x_{ref})-f(x_+)\|_2^2 - \|\min_{x^-_{skilled}\in\mathcal{T}_{batch}} f(x_{ref})-f(x^-_{skilled})\|_2^2))$$

where α determines how farther we want random forgeries to be from the genuine than skilled forgeries. In these two losses, batch hard triplet mining strategy and soft margin are also introduced. For reference, see [2].

Final loss (weighted sum):

$$\mathcal{L} = \sum_{\mathcal{T}_{batch}} \lambda\,\mathcal{L}_{skilled} + (1-\lambda)\,\mathcal{L}_{random}$$

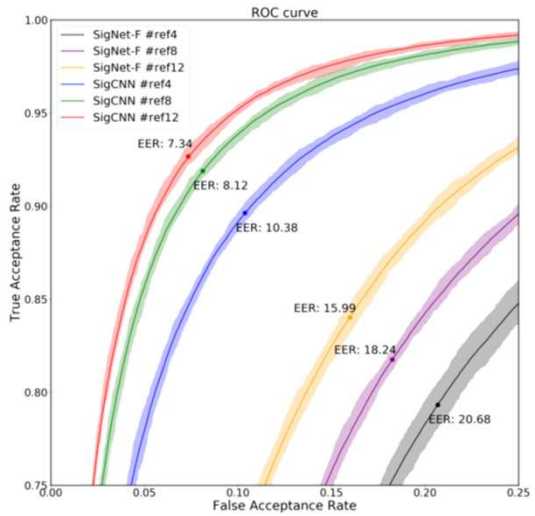
Results

- **Comparison with state of the art**

Reference	Type	#Refs	Method	EER(%)
Soleimani et al. [35]	WD	10	HOG+DMML	12.14
Ferrer et al. [36]	WI	10	LBP+SVM	16.44
Serdouk et al. [37]	WD	10	HOT+AIRSV	16.68
Zhang et al. [29]	WD	10	GAN	14.79
Hafemann et al. [12]	WD	5	SigNet-F$_{\text{user }\tau}$ (pre-trained)	24.91
Hafemann et al. [12]	WD	12	SigNet-F$_{\text{user }\tau}$ (pre-trained)	16.98
Hafemann et al. [12]	WD	4	SigNet-F$_{\text{user }\tau}$	16.25(±0.27)
Hafemann et al. [12]	WD	8	SigNet-F$_{\text{user }\tau}$	13.48(±0.34)
Hafemann et al. [12]	WD	12	SigNet-F$_{\text{user }\tau}$	12.10(±0.28)
Ours	WI	4	SigCNN	10.38(±0.23)
Ours	WI	8	SigCNN	8.12(±0.15)
Ours	**WI**	**12**	**SigCNN**	**7.34(±0.25)**

Comparison with state of the art on GPDS Synthetic dataset. WD means writer dependent, which usually requires two step verification: first a feature is extracted; then classification (usually SVM) algorithms are used. Our method is writer independent (WI), which is trained in an end-to-end fashion.

- **ROC curve**



ROC curve of our model and SigNet-F models proposed by [3] on the GPDS Synthetic dataset, given different number of reference samples.

Reference:

[1] "Facenet: A unified embedding for face recognition and clustering". F. Schroff, D. Kalenichenko, and J. Philbin, CVPR, 2015
[2] "In defense of the triplet loss for person re-identification". A. Hermans, L. Beyer, and B. Leibe, arXiv preprint arXiv: 1703.07737, 2017.
[3] "Learning features for offline handwritten signature verification using deep convolutional neural networks". L. Hafemann, R. Sabourin, and L. Oliveira, Pattern Recognition, 2017