SWIS: SELF-SUPERVISED REPRESENTATION LEARNING FOR WRITER INDEPENDENT OFFLINE SIGNATURE VERIFICATION

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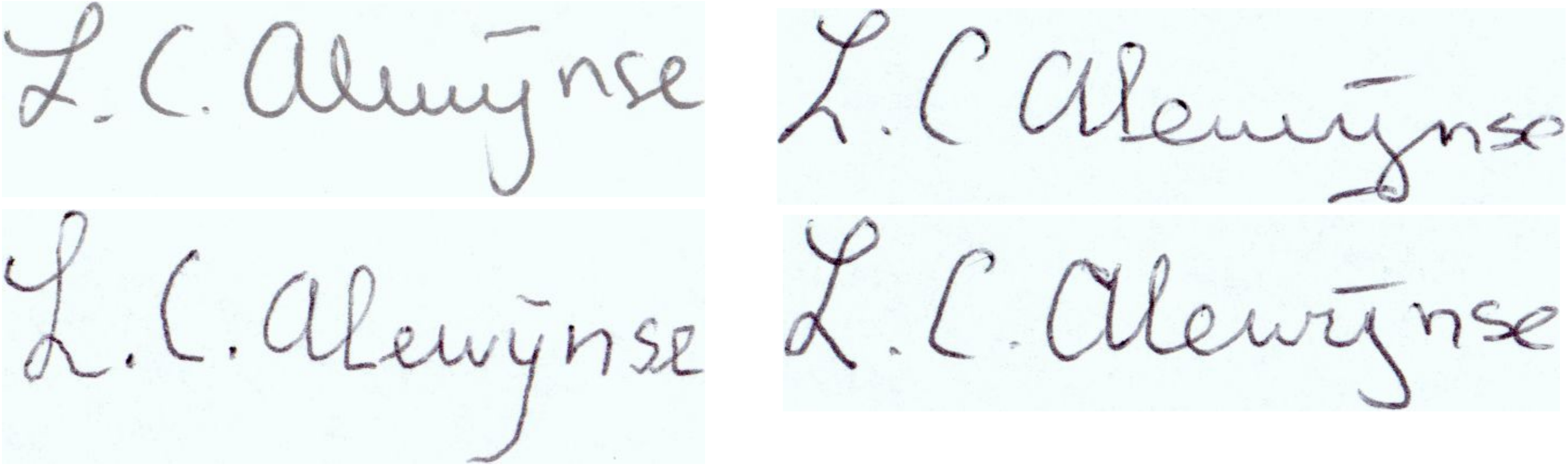
1. The fundamental constituent of signatures is “strokes”. Strokes of same letter vary from person to person.

2. Each signature is made up of a number of strokes, shifted by spatial coordinates.

3. The primary motivation is to learn representations such that a signature image can be represented in terms of decorrelated stroke information.



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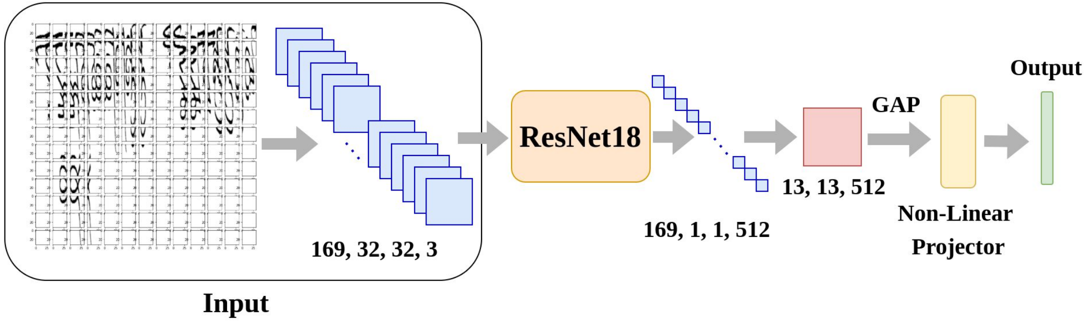
Pre-training Task

1. We divide each signature image into 169 patches (32 X 32) with an overlap of 16 pixels.

2. The patches are then passed through the ResNet18 [1] encoder and again reshaped to 13 X 13, such that each pixel in the output feature map represent each patch in the input, or each stroke.

3. Global Average Pooling is applied over the feature map and then passed through the projector to obtain the final feature vector.



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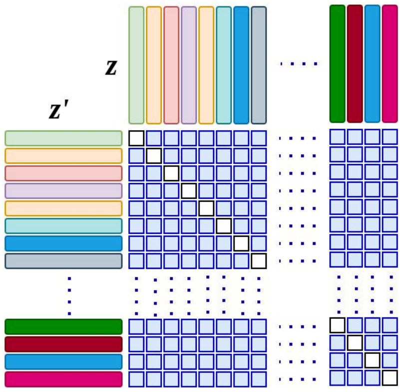
Loss Function

1. The loss function is of similar mathematical form as Barlow Twins [2] framework.

2. We diagonalize the cross-covariance matrix instead of the cross-correlation matrix as in Barlow Twins framework.

3. We L2 normalize the features and subtract the mean along the batch dimension.



$$\mathcal{L}_C = \frac{1}{N}\sum_{i=1}^{D}\left(\sum_{\substack{j=1\\ j\neq i}}^{D}\left(\sum_{k=1}^{N} z_k^i \cdot z'^j_k\right)^2 + \left(\sum_{k=1}^{N} z_k^i \cdot z'^i_k - 1\right)^2\right)$$

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Downstream Task

1. The downstream task in this work does not involve fine-tuning.

2. We extracted the features of the signature images from the frozen encoder and trained an SVM using the reference genuine signature images.

3. If the classifier predicted a forged signature of a writer as a different writer, then we considered it a correct prediction.

4. If the classifier predicted a genuine signature of a writer as a different writer, then we considered it a wrong prediction.

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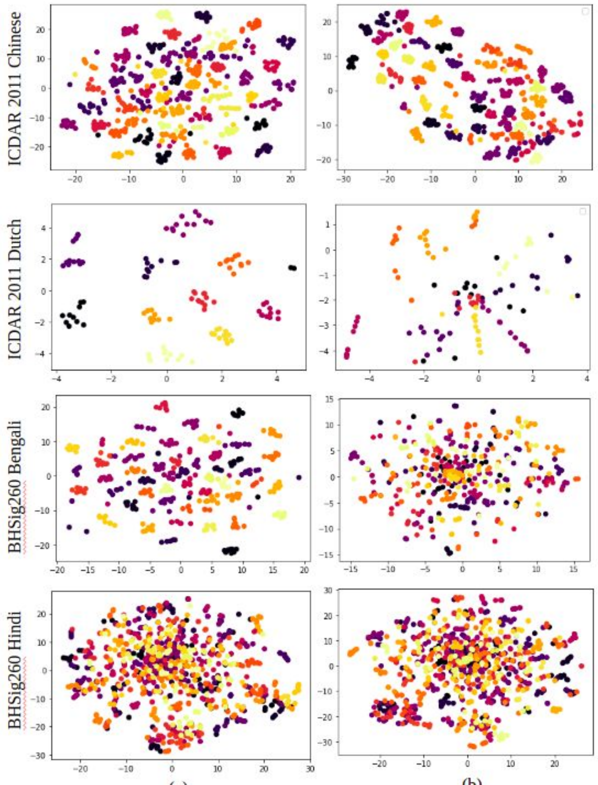
1. The image on the right hand side shows the comparison of clustering efficiency of the proposed method and SimCLR [3].

2. We can see that the clustering is better for the proposed method.



(a) (b)

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Below we can see the comparison of performance of SimCLR [3] and the proposed framework on 4 datasets, after pre-training and SVM classifier training on reference genuine signature images.

Method	ICDAR 2011 Dutch [8]			ICDAR 2011 Chinese [8]			BHSig260 Bengali [4]			BHSig260 Hindi [4]		
	Accuracy (%)	**FAR**	**FRR**	**Accuracy (%)**	**FAR**	**FRR**	**Accuracy (%)**	**FAR**	**FRR**	**Accuracy (%)**	**FAR**	**FAR**
SimCLR [3]	69.46	0.554	0.060	59.76	0.431	**0.317**	**73.45**	**0.117**	0.543	**72.45**	**0.103**	0.599
Proposed	**77.62**	**0.316**	**0.133**	**64.68**	**0.278**	0.583	72.04	0.367	**0.116**	72.43	0.104	**0.598**

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Below we show the comparison of the proposed framework with some supervised models on Bengali and Hindi datasets.

Method	BHSig260 Bengali [4]			BHSig260 Hindi [4]		
	Accuracy (%)	FAR	FRR	Accuracy (%)	FAR	FRR
Pal et al. [4]	66.18	0.3382	0.3382	75.53	0.2447	0.2447
Dutta et al. [6]	84.90	0.1578	0.1443	85.90	0.1310	0.1509
Dey et al. [5]	86.11	0.1389	0.1389	84.64	0.1536	0.1536
Alaei et al. [7]	–	0.1618	0.3012	–	0.1618	0.3012
Proposed	**72.04**	**0.367**	**0.116**	**72.43**	**0.104**	**0.598**

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Ablations on Hyperparameters on CEDAR [9] Dataset

Ablation type	Accuracy (%)	FAR (%)	FRR (%)
Best	83.8	11.8	18.7
Test Time AWGN $\mathcal{N}(0.0, 0.01)$	76.84	32.42	17.0
Test Time Random Cropping	79.3	34.4	11.57

1. Effect of change in Projector Depth : No discernible change in performance
2. Effect of change in pixel overlap between patches : Improvement in performance (1.2% increase in ACC for increase in 8 pixels of overlap, from 82.6% for 0 pixels to 83.8% for 8 pixels)
3. Effect of removal of Color Jitter augmentation : Degradation in performance (0.7% decrease in ACC, 83.1%)

Conclusion

1. The proposed work does perform at par with SimCLR.

2. In comparison to the Supervised Learning algorithms, there is a lot of room for improvement for the proposed self-supervised framework.

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Thank You