Offline Writer Identification Using Convolutional Neural Network Activation Features

Pattern Recognition Lab (CS 5)
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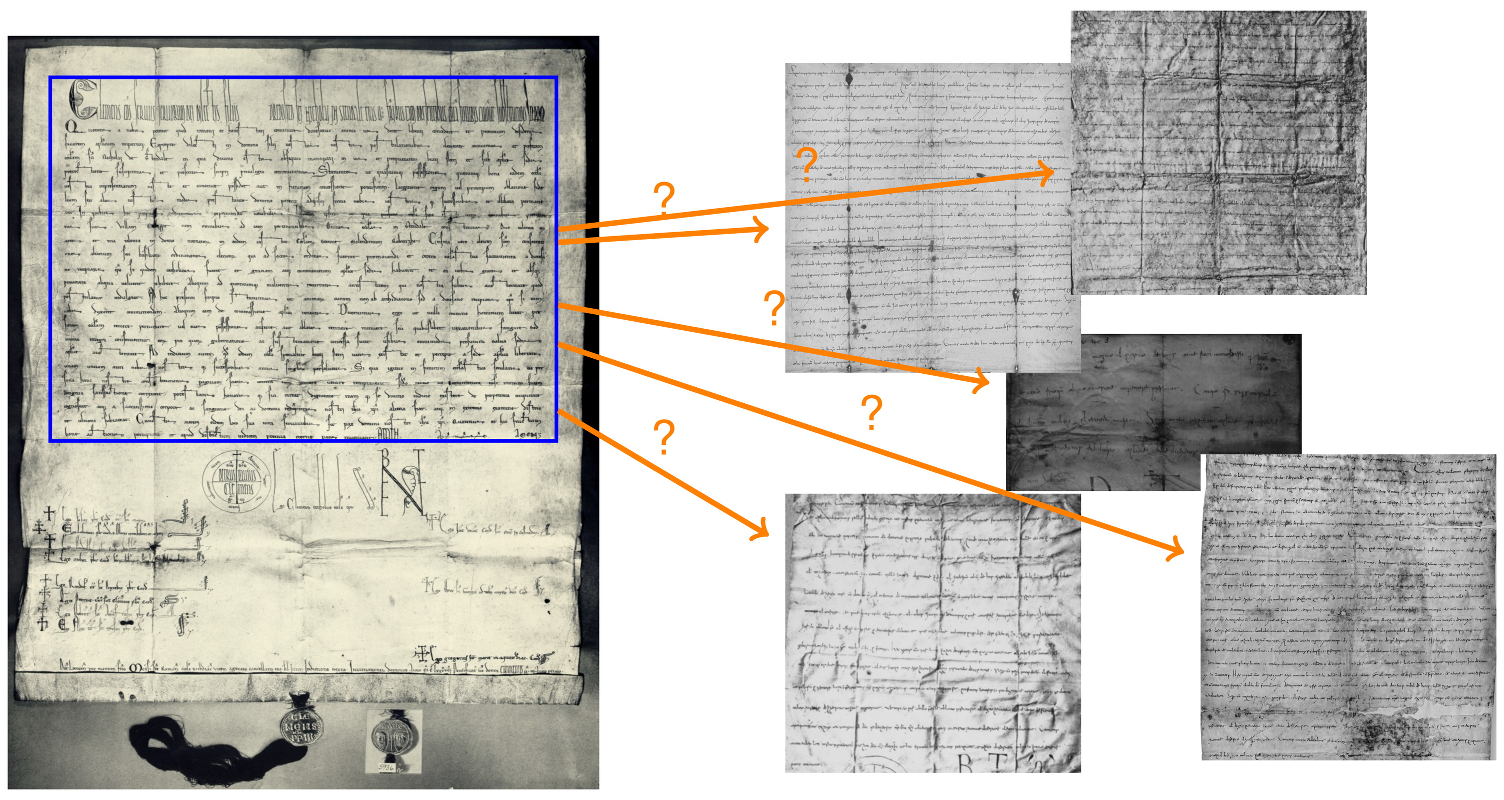
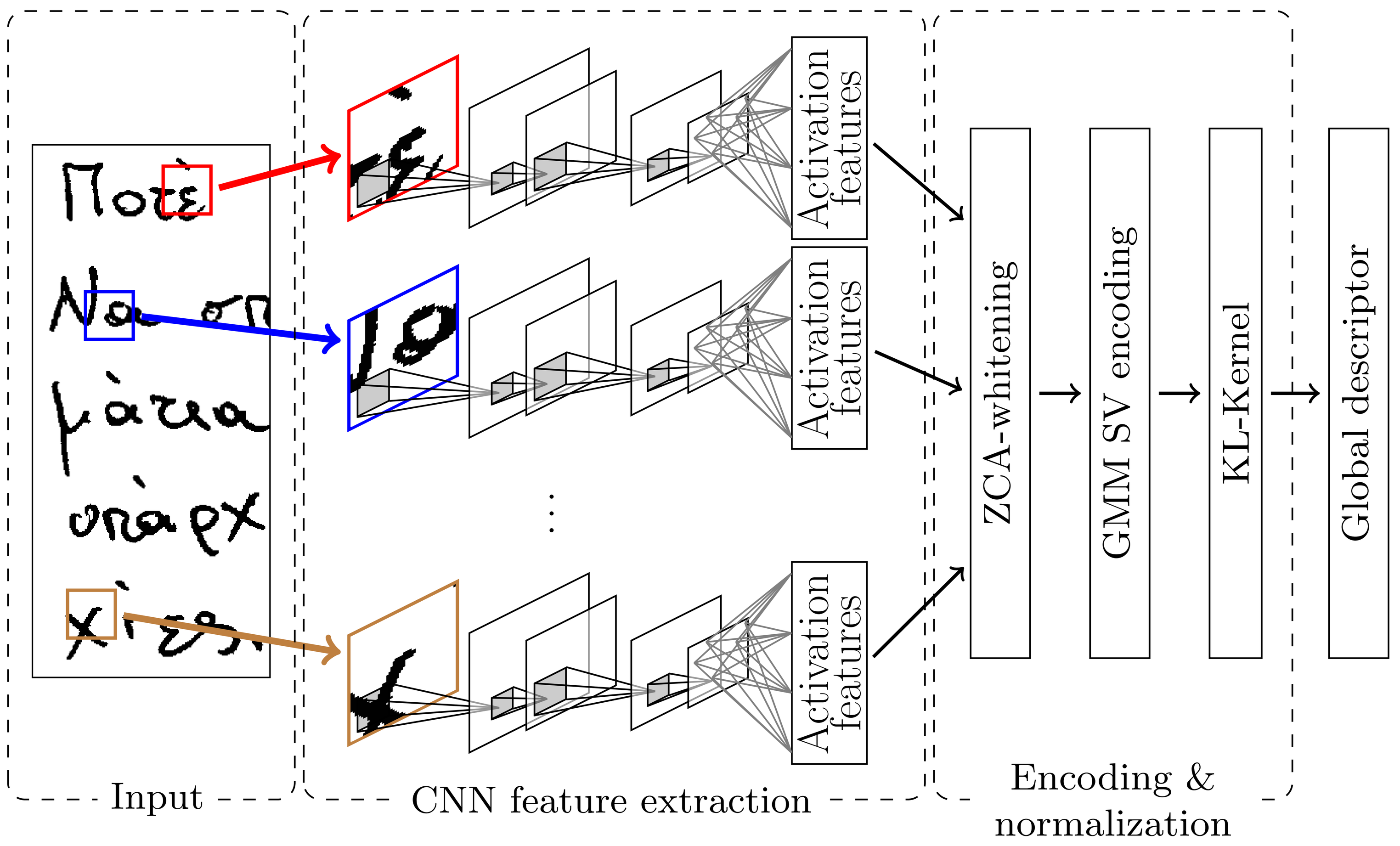
Motivation

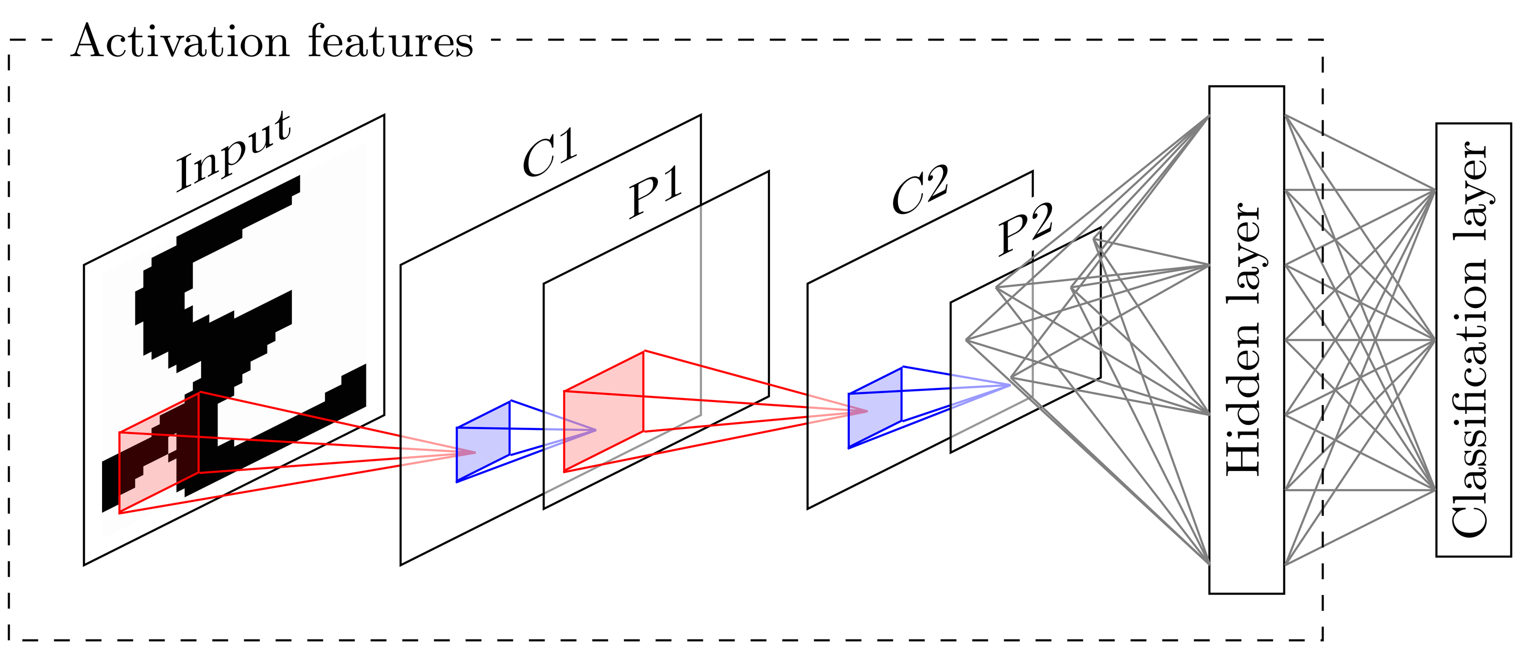


[Image source: Göttingen Academy of Sciences and Humanities]

Method Overview



CNN Activation Features



Parameter Evaluation

CNN configurations

Filter configuration	C1	P1	C2	P2
A	5×5	2×2	5×5	2×2
B	7×7	2×2	5×5	3×3

Classification accuracy of the CNN (train / test)

	# hidden nodes		
	64	128	256
A	38.2 / 23.2	49.3 / 23.7	55.0 / 24.5
B	40.3 / 21.0	45.6 / 22.4	53.5 / 23.0

Averaged mAP of VLAD

	# hidden nodes		
	64	128	256
A	93.7	92.6	89.5
B	94.8	92.9	91.0

Encoding

GMM Supervectors [1]

Local Descriptors: $\boldsymbol{X} = \{\boldsymbol{x}_1, \ldots, \boldsymbol{x}_T\}$

Background model: GMM with K weighted Gaussians $g_k(\boldsymbol{x}) := \mathcal{N}(\boldsymbol{x}; \boldsymbol{\mu}_k, \Sigma_k)$

Mean adaptation:

$$\hat{\boldsymbol{\mu}}_k = \frac{1}{n_k}\sum_{t=1}^{T}\gamma_t(k)\boldsymbol{x}_t\,, \quad \text{where } n_k = \sum_{t=1}^{T}\gamma_t(k)\,; \quad \gamma_t(k) = \frac{w_k g_k(\boldsymbol{x}_t)}{\sum_{j=1}^{K} w_j g_j(\boldsymbol{x}_t)}$$

Mixing: $\tilde{\boldsymbol{\mu}}_k = \alpha_k\hat{\boldsymbol{\mu}}_k + (1-\alpha_k)\boldsymbol{\mu}_k\,,$ where $\alpha_k = \frac{n_k}{n_k+\tau}$ [τ: relevance factor]

GMM Supervector: $\boldsymbol{s} = (\tilde{\boldsymbol{\mu}}_1^\top, \ldots, \tilde{\boldsymbol{\mu}}_K^\top)^\top$

Postprocessing

Normalize with kernel derived from the KL divergence: $\mathring{\boldsymbol{\mu}}_k = \sqrt{w_k}\boldsymbol{\sigma}_k^{-\frac{1}{2}}\tilde{\boldsymbol{\mu}}_k$

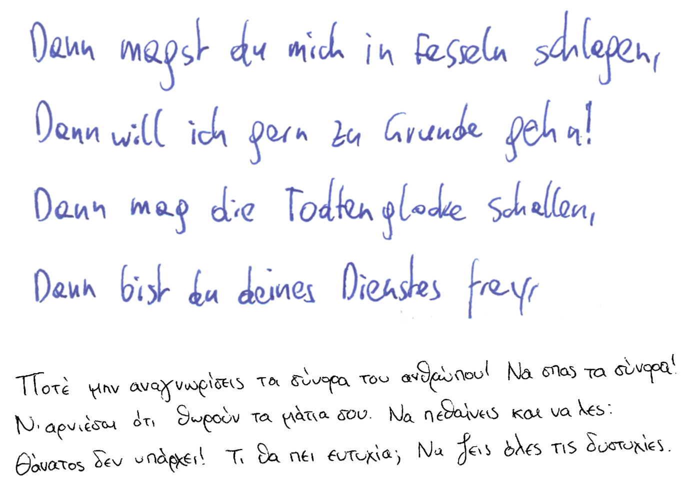
Datasets

CVL

- 310 writers (training: 27, test: 283)
- 5 forms (1 German, 4 English)

ICDAR13

- 350 writers (training: 100, test: 250)
- 4 forms (2 English / 2 Greek)



Evaluation

Hard criterion and mAP evaluated on ICDAR13 (test set)

	TOP-1	TOP-2	TOP-3	mAP
CS [2]	95.1	19.6	7.1	NA
SV [1]	97.1	42.8	23.8	67.1
SURF	96.7	55.1	27.3	71.8
Proposed	**98.9**	**83.2**	**61.3**	**88.6**

Hard criterion and mAP evaluated on CVL (test set)

	TOP-1	TOP-2	TOP-3	TOP-4	mAP
Comb. [3]	**99.4**	98.3	94.8	82.9	96.9
SV [1]	99.2	98.1	95.8	88.7	97.1
SURF	98.6	97.3	94.8	83.6	95.8
Proposed	**99.4**	**98.8**	**97.3**	**92.6**	**97.8**

Conclusion

- CNNs learn writers' characteristics effectively
- KL-normalized GMM supervectors are very good for encoding local CNN activation features
- Method is comparable or better than s. o. t. a. on ICDAR13 and CVL

References

[1] Vincent Christlein et al. "Writer Identification and Verification using GMM Supervectors". In: *Applications of Computer Vision, IEEE Winter Conference on.* 2014, pp. 998–1005.

[2] Rajiv Jain and David Doermann. "Writer Identification Using an Alphabet of Contour Gradient Descriptors". In: *Document Analysis and Recognition (ICDAR), International Conference on.* 2013, pp. 550–554.

[3] Rajiv Jain and David Doermann. "Combining Local Features for Offline Writer Identification". In: *Frontiers in Handwriting Recognition, 14th International Conference on.* 2014, pp. 583–588.