ECG-based Biometrics using a Deep Autoencoder for Feature Learning: An Empirical Study on Transferability

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Contributions

A single-channel ECG biometric system with an autoencoder as feature extractor is proposed and evaluated on data from a local hospital.

- A lower dimensional representation of heartbeat templates is learned and a superior performance is achieved.
- A transfer learning setting is explored and results show practically no loss of performance, suggesting that it can be deployed in systems with offline training: small to large-scale deployments, including embedded applications.

Autoencoder

- A neural network (NN) that learns to reconstruct the inputs belonging to a given dataset $\mathcal{X}_\star$: $X = [\{x : x \in \mathcal{X}_\star \subset \mathcal{X}\}]^\top$.
- It consists of an encoder, $\lambda : \mathcal{X} \mapsto \mathcal{Z}$, and a decoder, $\psi : \mathcal{Z} \mapsto \mathcal{X}$.
- To update the function parameters via backpropagation, an objective function, $\mathcal{L}(X, \lambda, \psi)$ must be defined, e.g. $\mathcal{L}(X, \lambda, \psi) = ||X - \hat{X}||_F^2$, where $\hat{X} = [\{\hat{x} : \hat{x} = (\psi \circ \lambda)(x), \forall x \in \mathcal{X}_\star\}]^\top$ denotes the reconstructed inputs.

Regularization is required to learn useful representations [1]:

- explicitly design a network with a bottleneck (undercomplete);
- add regularization terms to the objective function;
- use techniques such as data corruption or dropout.

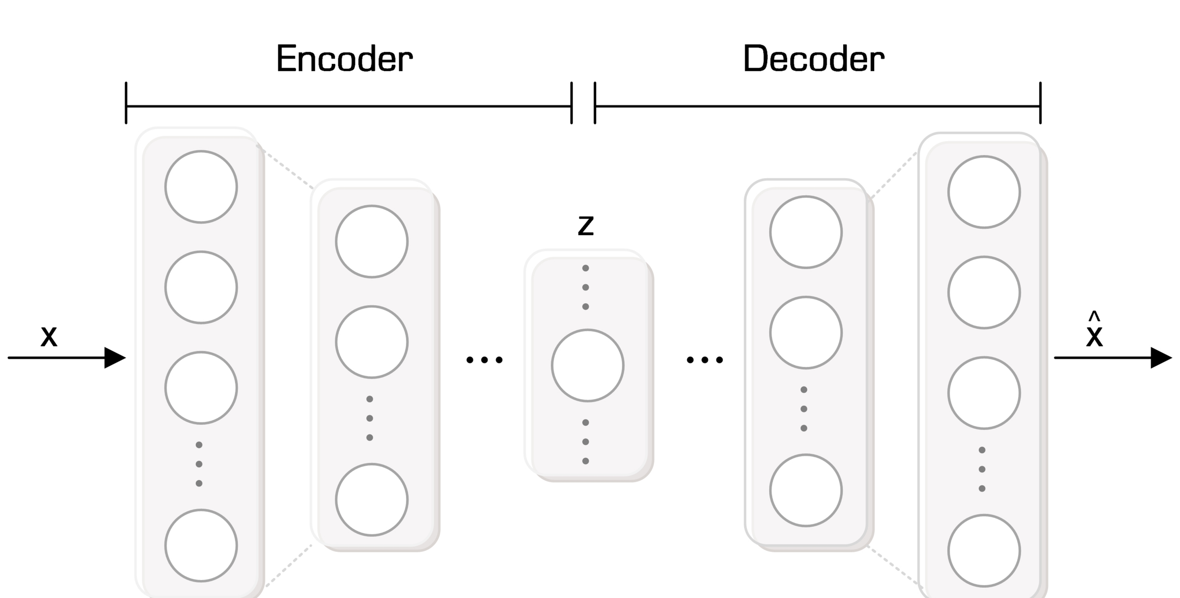

Figure 1: Schematic of an undercomplete autoencoder.

Biometric Identification System

A one-to-many template matching system whose templates are given by an encoded representation of individual ECG heartbeats. The raw signals are bandpass filtered. Heartbeat templates are built by taking a fixed-length window around detected R peaks. The mapping function is learned by the encoder submodule of the autoencoder and its hyperparameters are selected using a validation set. The parameters of the classifier (k-Nearest Neighbor) are fixed.

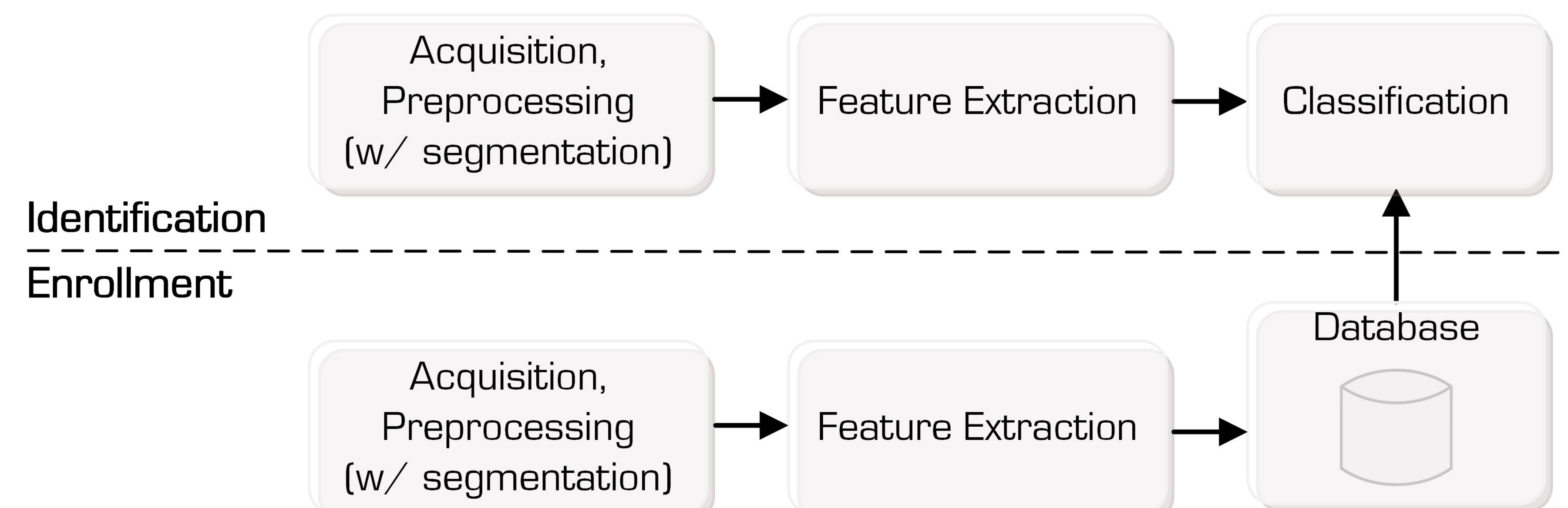

Figure 2: Template matching biometric system [2].

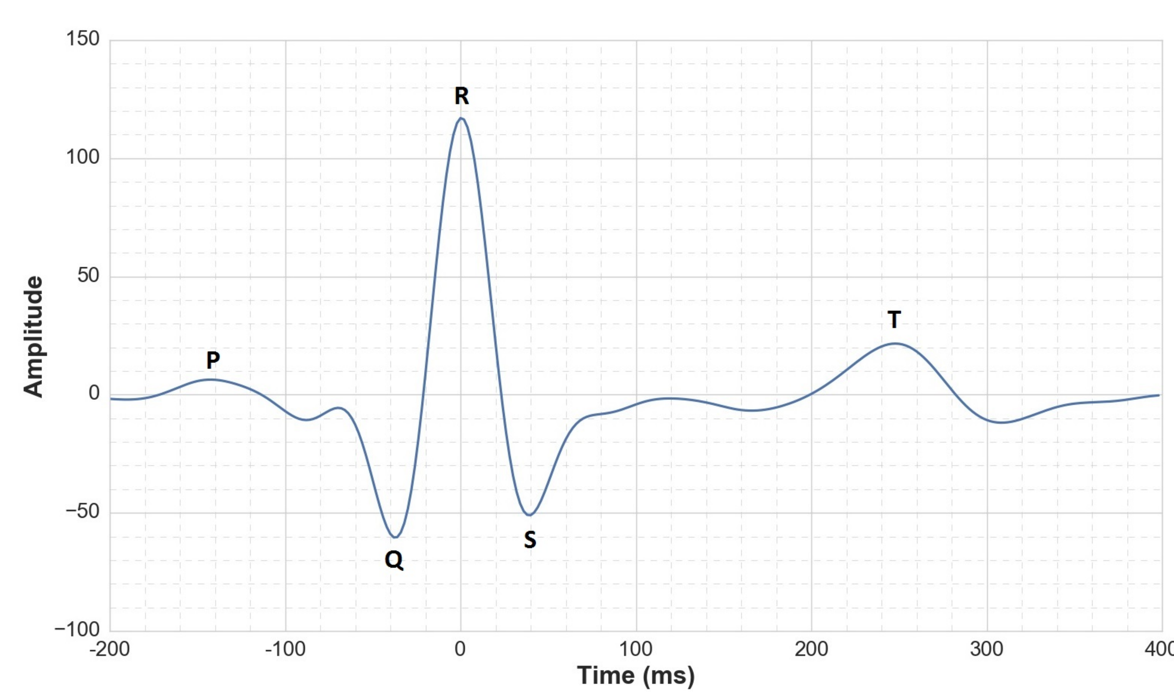

Figure 3: Heartbeat template.

Learning Schemes

- **B**: identity function as feature extractor, i.e. templates are not encoded.
- **M1**: autoencoder is trained only on the target dataset, i.e. templates from enrolled subjects.
- **M2**: autoencoder is trained only on leftover data, i.e. templates from unenrolled subjects. Transfer learning scenario.
- **M3**: autoencoder is trained on all available data, i.e. templates from enrolled and unenrolled subjects. Adds insight on how the system behaves in the presence of additional data.

Results

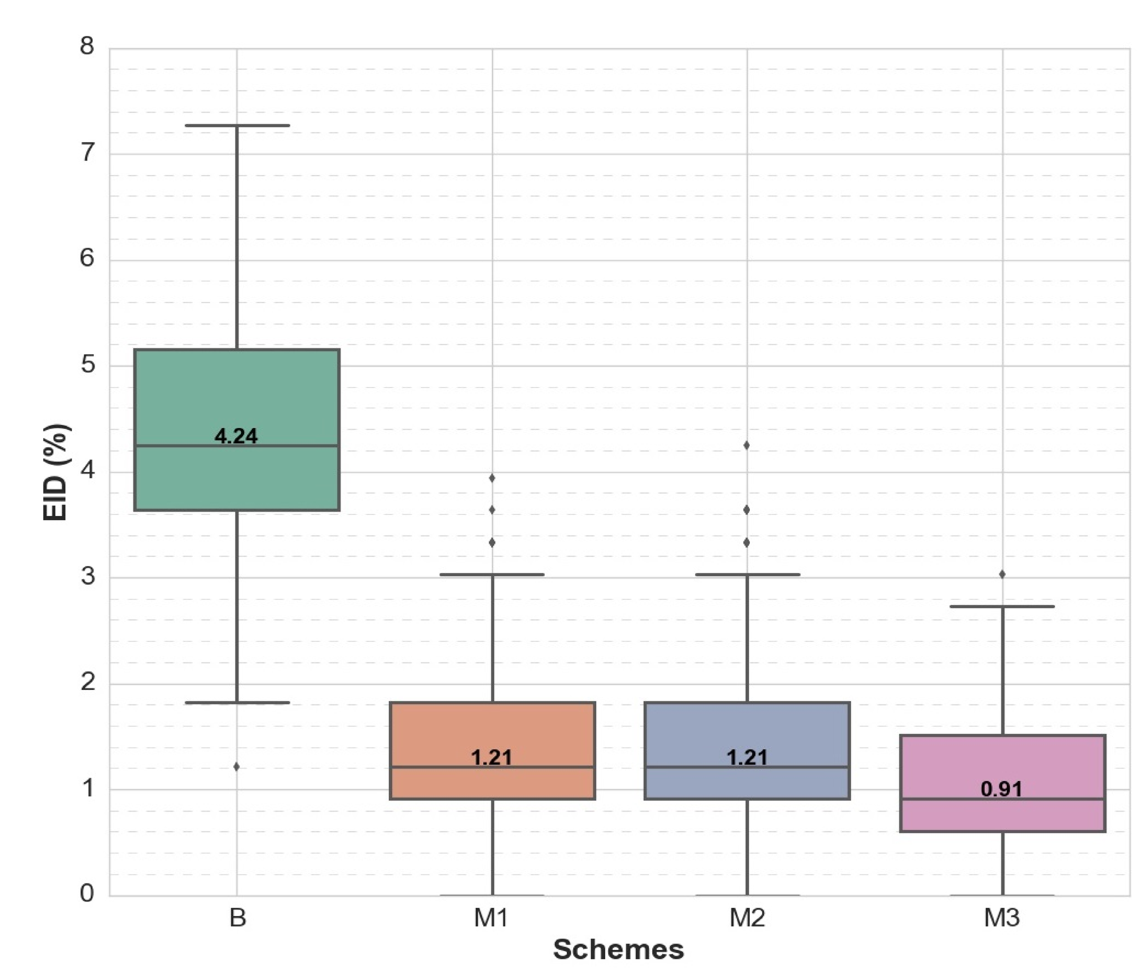

Figure 4: Identification error: boxplots with annotated medians.

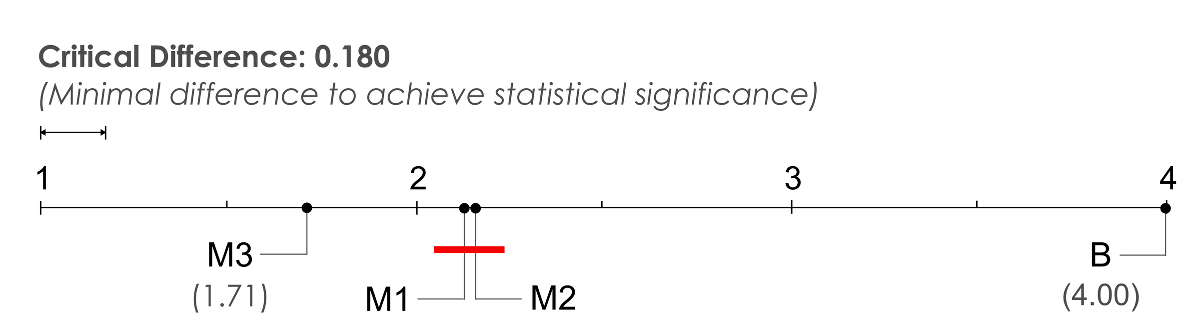

Figure 5: Scheme ranking (Nemenyi test [3]).

Future Research

- ECG as dynamical system: state-space signal processing using Bayesian filtering [4, 5].
- Data augmentation: simple translations or scaling; models capturing the ECG dynamics [4]; general generative models [6, 7].
- Different biometric systems: deep learning based (Convolutional NN, Recurrent NN); feature fusion; ensembles.

References

[1] Ian Goodfellow, et al., *Deep Learning*, MIT Press, 2016.

[2] Antonio Fratini, et al., Individual identification via electrocardiogram analysis, *Biomedical Engineering Online*, 14(1), 2015.

[3] Janez Demšar, Statistical Comparisons of Classifiers over Multiple Data, *Journal of Machine Learning Research*, 7(Jan), 2006.

[4] Patrick McSharry, et al., A Dynamical Model for Generating Synthetic Electrocardiogram Signals, *IEEE Transactions on Biomedical Engineering*, 50(3), 2003.

[5] Reza Sameni, et al., A nonlinear Bayesian filtering framework for ECG denoising, *IEEE Transactions on Biomedical Engineering*, 54(12), 2007.

[6] Diederik Kingma, et al., Auto-Encoding Variational Bayes, in *International Conference on Learning Representations (ICLR)*, 2014.

[7] Ian Goodfellow, et al., Generative Adversarial Nets, in *Adv. Neural Information Proc. Systems (NIPS)*, 2014.

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