Variable Projection Networks for Arrhythmia Detection Joint Annual Conference of the Austrian, German, and Swiss Societies for Biomedical Engineering (BMT 2022)

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# Outline

# Motivation

Methodology

## Results

# Conclusion



Methodology



# General motivations

Motivation

# Deep learning (DL) approaches

- Data-driven black box models with usually unexplainable output.
- Huge performance gain in many applications.
- Resource (data, computing, memory) intensive methods.

# Model-based approaches

- White box models with usually transparent decisions.
- Incorporates domain knowledge via mathematical modeling.
- Tradeoff between performance and interpretability.
- Manageable resource requirements.

# Idea: train VP + NNs in a model-driven learning framework

- VP: automatic feature extractor with interpretable parameters
- NN: learn and model non-linear and complex relationships



# Methodology



# Orthogonal transformations

#### Methodology

Linear signal modeling:

$$x \approx \tilde{x} = \sum_{k=0}^{n-1} c_k \Phi_k = \Phi c \qquad (x \in \mathbb{R}^N)$$

Best approximation problem in Hilbert spaces:  $S := \operatorname{span}\{\Phi_0, \Phi_1, \dots, \Phi_{n-1}\} \subset \mathbb{R}^N \text{ generated subspace}$   $\operatorname{dist}(x, S) := \min_{u \in S} \|x - y\|_2 = \|x - \tilde{x}\|_2$ 

- Solution to the discrete case (linear least squares):
  - Coefficients vector:  $c = \Phi^+ x$
  - Orthogonal projection:  $\tilde{x} = P_{\mathcal{S}}x = \Phi\Phi^+x$

Orthogonal transformations with system  $\Phi$ , e.g.: trigonometric, Hermite [1], etc.



[1] Sörnmo, L., Börjesson, P.L., Nygards, M. E., Pahlm, O., A method for evaluation of QRS shape features using a mathematical model for the ECG, *IEEE Trans. on Biomed. Eng.*, 1981;28:713–717.

## Parameterized orthogonal transformations

#### Methodology

Nonlinear signal modeling:

$$x \approx \tilde{x} = \sum_{k=0}^{n-1} c_k \Phi_k(\theta) = \Phi(\theta)c \qquad (x \in \mathbb{R}^N)$$

- Variable projection problem [2]:  $S(\theta) := \operatorname{span} \{ \Phi_0(\theta), \Phi_1(\theta), \dots, \Phi_{n-1}(\theta) \} \subset \mathbb{R}^N$  generated subspace  $\min_{\theta} \operatorname{dist}(x, S(\theta)) := \min_{\theta} \|x - \Phi(\theta)\Phi^+(\theta)x\|_2$
- Solution to the discrete case (nonlinear least squares):
  - Coefficients for a given  $\theta \in \mathbb{R}^m$ :  $c = \Phi^+(\theta)x$
  - Parameterized orthogonal projection:  $\tilde{x} = P_{\mathcal{S}(\theta)}x = \Phi(\theta)\Phi^+(\theta)x$

 $\theta$  usually represents interpretable quantities, e.g., attenuation, shape parameters.

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  $+...+$  =

<sup>[2]</sup> G. H. Golub, V. Pereyra. The differentiation of pseudo-inverses and nonlinear least squares problems whose variables separate. *SIAM J. on Numerical Analysis*, 1973.

# Artificial neural networks (ANN) Methodology

# Advantages

- Mathematical model of biological neurons.
- Theoretically approved by the universal approximation theorems.
- Easy to train due to its differentiability.



Figure: Artificial neuron model.

# Spiking neural networks (SNN) Methodology

### Advantages

- Biologically plausible neuron model.
- Power efficiency due to the sparsity of the output spike trains.
- Reduced number of floating point operations due to binary output.



Figure: Leaky integrate-and-fire (LIF) neuron model.

# VPNet architecture for spikelike waveforms Methodology

System of Hermite polynomials:  $\{h_k \mid k \in \mathbb{N}\}$ .

System of Hermite functions:

$$\Phi_k(t) = h_k(t) / ||h_k||_2 \cdot e^{-t^2/2} \qquad (k \in \mathbb{N}).$$

- Nonlinear parameters: dilation and translation  $heta = [ au, \lambda]^T$
- Parametrization:

$$\Phi_k(\tau,\lambda;t) := \sqrt{\lambda} \cdot \Phi_k \left(\lambda(t-\tau)\right) \quad (t,\tau \in \mathbb{R}, \lambda > 0)$$



# VPNet architecture for spikelike waveforms Methodology



Figure: Output of a trained VP layer: for a normal beat (a) and two abnormal beats (b)-(c).

#### **VPNet** architectures

- VP + ANN [3]
- VP + SNN [4]

[3] Kovács, P., Bognár, G., Huber, C., Huemer, M., VPNet: Variable Projection Networks, *International Journal of Neural Systems (IJNS)*, pp. 2150054-1–19, 2021.

[4] Kovács, P., Samiee, K., Arrhythmia detection using spiking variable projection neural networks, *Computing in Cardiology (CinC)*, pp. 1–4, 2022.



Methodology



# Classification of real ECG heartbeat signals



- PhysioNet MIT-BIH Arrhythmia Database
- Normal ↔ ventricular ectopic heartbeats
- Balanced dataset: 4260-4260 beats (train), 3220-3220 (test)

#### Table: Overall Classification performances of different NN architectures.

Architecture	Acc%	Spec%	Sens%
ANN	94.32%	95.53%	93.11%
CNN	95.92%	96.09%	95.75%
SNN	95.59%	93.73%	<b>97.45</b> %
SCNN	95.42%	95.31%	95.53%
VPANN	96.65%	96.83%	96.61%
VPSNN	96.61%	99.10%	94.13%
VPTSNN	97.16%	99.60%	94.72%
MVPSNN	94.55%	96.52%	92.58%
VPCSNN	95.61%	98.07%	93.14%

Table: Total number of parameters and inference memory size of different NN architectures.

Architecture	# of parameters	memory size
ANN	59010	234  KB
CNN	212610	967 KB
SNN	58880	231 KB
SCNN	376704	1.5  MB
VPANN	39	0.7 KB
VPSNN	242	$5.3~{\sf KB}$
VPTSNN	242	$5.3~{\sf KB}$
MVPSNN	72	2.2 KB
VPCSNN	26	1.1 KB



Methodology



# Conclusion Conclusion

# Summary

- Novel model-based NN architecture for 1D signal processing
- Incorporated domain knowledge, e.g., Hermite-basis for QRS
- Compact network topology
- Fast and efficient implementation, e.g., neuromorphic devices
- Interpretable parameters, e.g., QRS location and width
- Preliminary results: performance comparable with state of the art with low computational cost.

### Further research

- More experiments: larger datasets, more classes, etc.
- New fields of applications: visually evoked potentials