Early detection of hippocampal sharp wave-ripples

Tomas Fiers, Jasper Wouters, Davide Ciliberti, Fabian Kloosterman, Alexander Bertrand

ESAT-STADIUS @ KU Leuven; Neuro-Electronics Research Flanders; VIB; Brain and Cognition, Imec -- Leuven, Belgium.

STADIUS Center for Dynamical Systems, Signal Processing and Data Analytics

nerf Empowered by imec, K.U.Leuven and VIB

Introduction

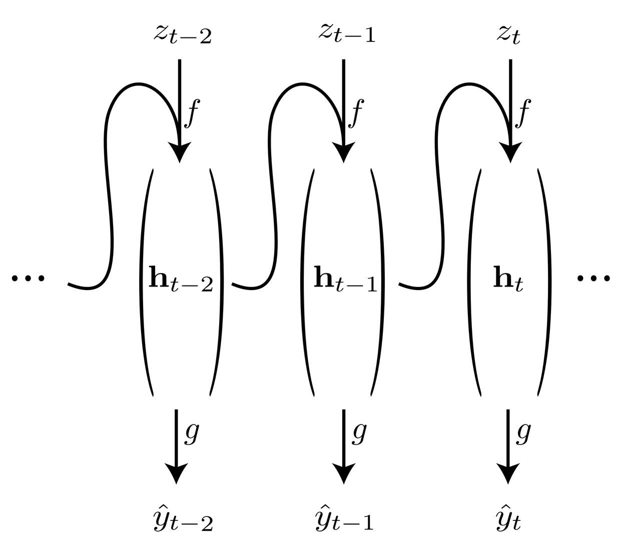
Closed-loop brain-computer interfaces require fast signal detectors.

Case in point: online detection of hippocampal sharp wave-ripples (SWR's)

- The SWR is a well-known motif in electrophysiological recordings of the mammalian hippocampus, strongly linked to learning and memory. The hippocampus has been shown to replay past experiences during SWR's.
- A powerful method to study these phenomena is to apply feedback stimulation specifically during SWR's, requirig real-time SWR detection.
- The state-of-the-art algorithm recognises SWR's quite late (see results). This compromises experimental power, particularly in SWR disruption experiments. We present a new algorithm that detects SWR's significantly faster.

Proposed SWR detector

Recurrent neural network (RNN) with gated recurrent units (GRU).
(K Cho et al, 2014). Single layer, 25 hidden units in $\mathbf{h}_t$



f $$\mathbf{h}_t = \mathbf{u}_t \odot \mathbf{h}_{t-1} + (1-\mathbf{u}_t) \odot \tilde{\mathbf{h}}_t$$

New state vector is weighted mean of previous state and candidate state ($\odot$ = elementwise *)

$$\tilde{\mathbf{h}}_t = \tanh\big(\mathbf{r}_t \odot \mathbf{W}_{hh}\mathbf{h}_{t-1} + \mathbf{w}_{zh}^T z_t + \mathbf{b}_h\big)$$
$$\mathbf{u}_t = \sigma(\mathbf{W}_{ha}\mathbf{h}_{t-1} + \mathbf{w}_{za}^T z_t + \mathbf{b}_a)$$
$$\mathbf{r}_t = \sigma(\mathbf{W}_{hr}\mathbf{h}_{t-1} + \mathbf{w}_{zr}^T z_t + \mathbf{b}_r)$$

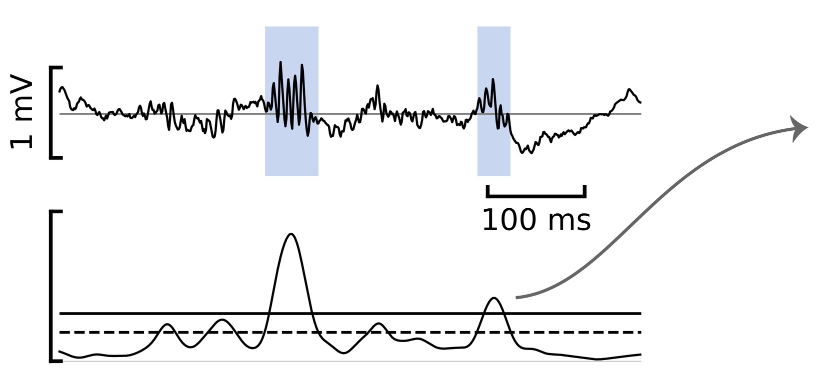
So called "update and reset gates" are classic perceptrons. Candidate state additionally uses "gating", or a tunable gain.

g $$\hat{y}_t = \sigma(\mathbf{w}_{hy}^T \mathbf{h}_t + b_y)$$

Output is again a classic perceptron: linear projection of the hidden state, shifting, and squashing to (0, 1)

Training the detector

1. Use a 27 minutes-long voltage recording as training data z_t
   N = 1 rat, 1 electrode, 1 session. Rat was resting.
   Data collected by *F Michon et al, 2016*
2. Label reference SWR segments, using conventional offline algorithm:

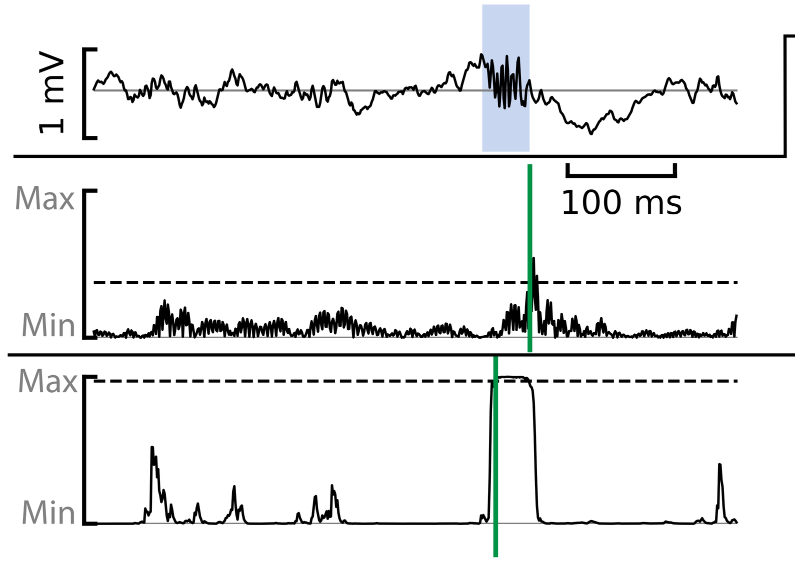


- Zero-lag (non-causal) band pass filter for ripple band, 100-250 Hz. Then:
- Envelope via Hilbert transform, smoothed with Gaussian kernel
- High threshold for SWR detection, lower threshold for SWR extent
- Discard segments shorter than 25 ms, Join segments closer than 10 ms

3. Convert these segments to a binary training signal y_t
   $y_t = 1$ within reference SWR segments, $y_t = 0$ outside them
4. Define a loss function ℓ_t which compares the RNN output $\hat{y}_t$ to the training signal y_t – Cross entropy (rewards similarity):
   $\ell(y_t, \hat{y}_t) = y_t \log(\hat{y}_t) + (1-y_t)\log(1-\hat{y}_t)$
5. Minimize $\langle \ell_t \rangle$ by tuning the parameters of the RNN (the weightings **W_**, **w_** and **b_** in f and g), via stochastic gradient descent (SGD)
   - Cut training data into 300 ms long chunks.
   - Per chunk: estimate partial derivatives of loss w.r.t. each RNN parameter via "backpropagation through time". (Using the *PyTorch* library).
   - Update weights via AdaMax SGD (*D Kingma et al, 2015*)
   - Repeat for all chunks, and for multiple passes over the training data
6. Prevent overfitting to the training data by early stopping on a held-out validation set
   7' of training data were used for validation, the other 20' for training proper

Quantifying performance

- Detect SWR segments with conventional offline method..
- ..in 7 minutes of test data (held out from any training)
- Result: 163 reference SWR segments
- **Detections** are threshold crossings of output envelopes (with a minimum distance of 34 ms between detections):

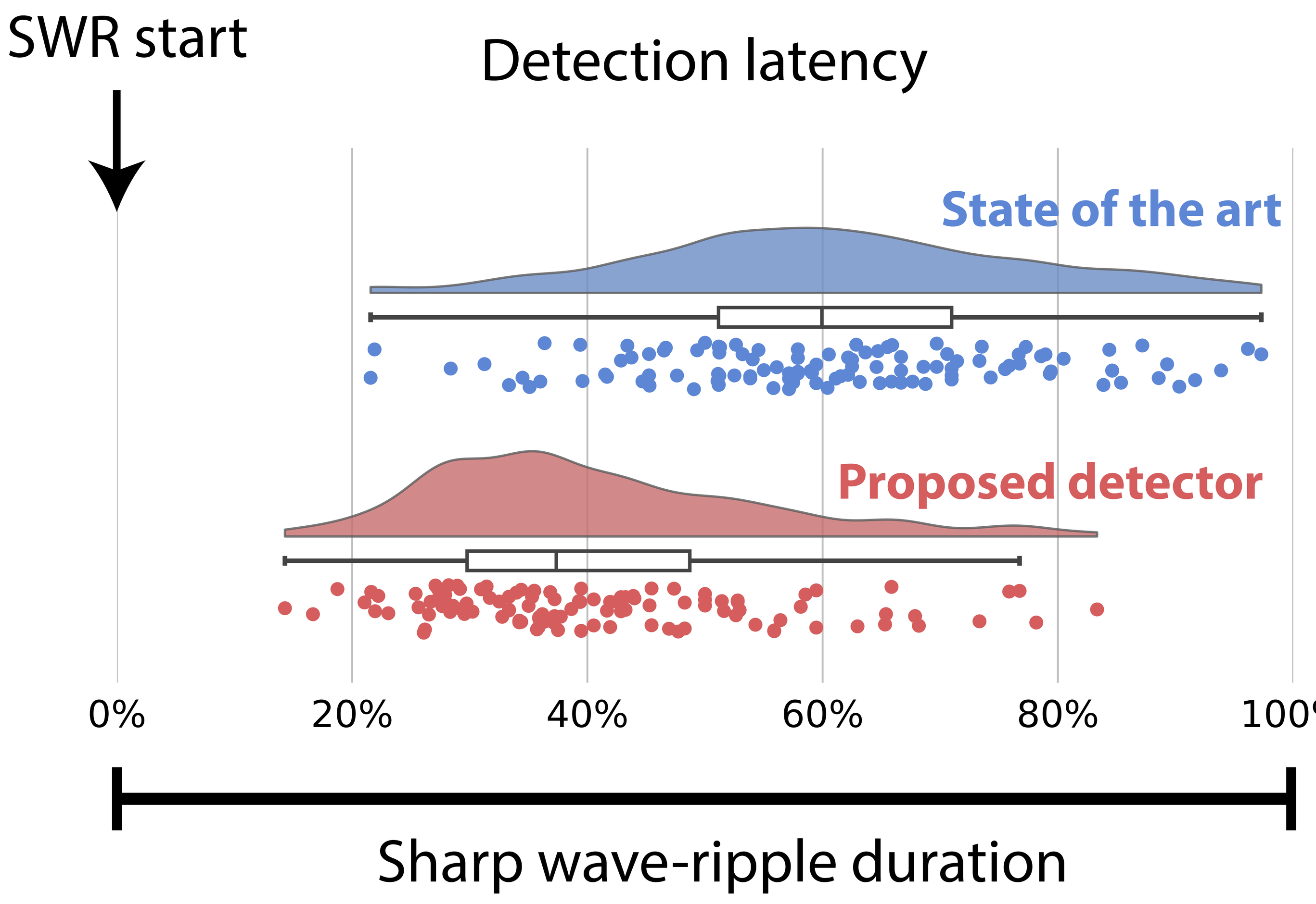


State of the art
Rectified output of online, causal band-pass filter (Chebyshev type 2 7th order IIR filter, 100 - 250 Hz, median group delay of 14 ms)

Proposed detector
Output of RNN $\hat{y}_t$

Proposed detector is faster

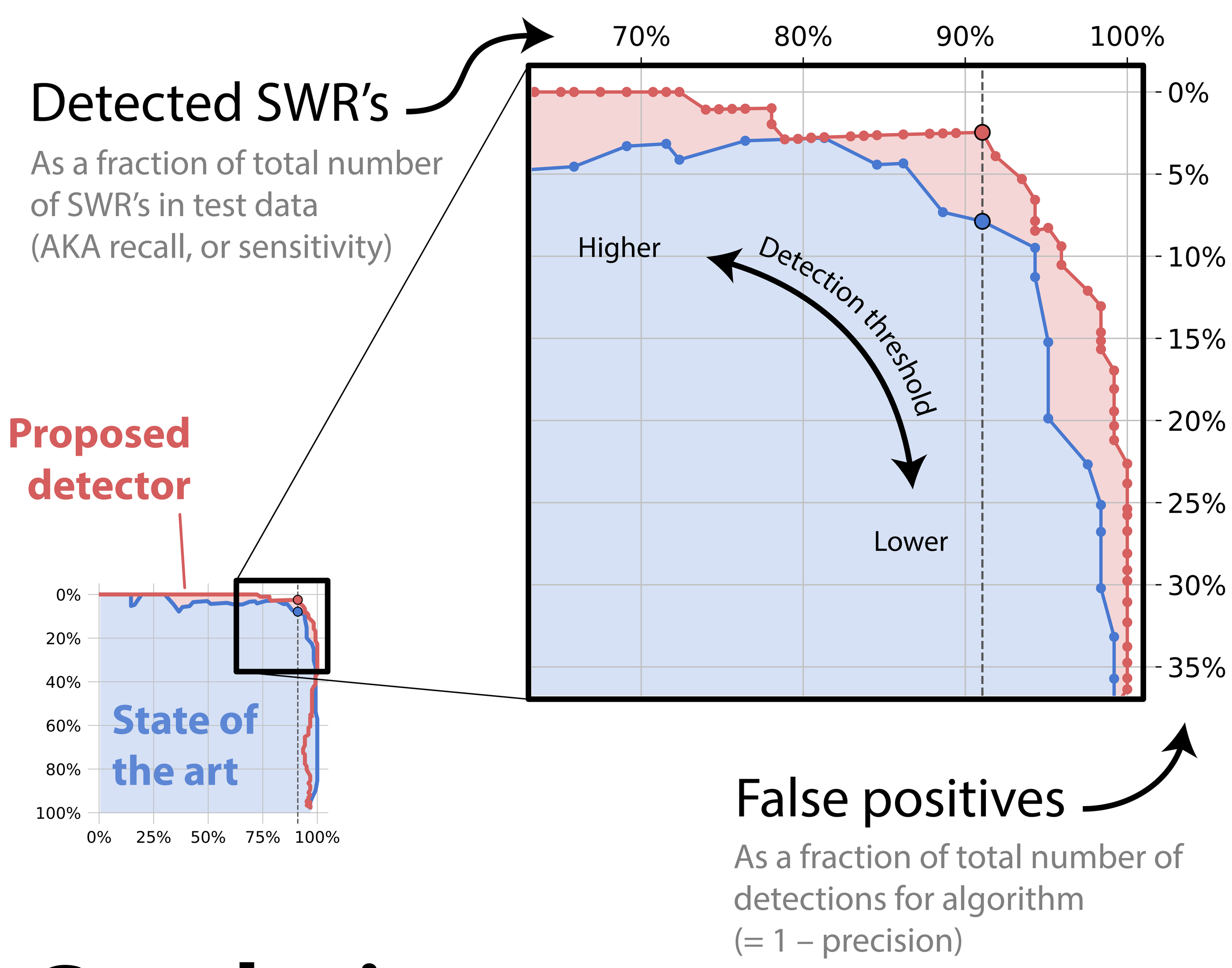
- For a threshold where both methods detect 91% of events..
- .. compare detection times with corresponding SWR segments:



- Median improvement in relative latency: 23 percentage points
- Median improvement in absolute latency: 9 ms

.. and more sensitive & precise

- Define an SWR as `detected` if detection event intersects SWR segment.
- Each theshold yields a different precision-sensitivity tradeoff:



Conclusion

- We presented a new algorithm to detect sharp wave-ripples.
- The algorithm is significantly faster than the state-of-the-art method, while being at least equally sensitive and precise.
- We thus enable more powerful closed-loop experiments based on SWR-detection.