# Estimation of Channel Distribution Functions using a Neural Network

Peter Hartig

March 12, 2020

The channel state perspective

The optimization framework

Extension of ViterbiNet: Reduced

Simulation Results

Molecular Communication Application

#### The Channel State

The true state of the channel, s[k], is hidden from us but we attempt to estimate this state based the sampled signal y[k].

#### The Channel State

The true state of the channel, s[k], is hidden from us but we attempt to estimate this state based the sampled signal y[k].

# **Sampling Channel State**

Consider some received signal y[k] sampled using some filter at the receiver of a point-to-point system.



## **Sampling Channel State**

Consider some received signal y[k] sampled using some filter at the receiver of a point-to-point system.



The channel is a random process that realizes a specific state for each time index k. Specifically give the example of the LTI channel.

# **Estimating the True Channel State**

The true state of the channel, s[k], is hidden from us but we attempt to estimate this state based the sampled signal y[k].

# **Estimating the True Channel State**

The true state of the channel, s[k], is hidden from us but we attempt to estimate this state based the sampled signal y[k].

The channel state perspective

The optimization framework

Extension of ViterbiNet: Reduced

Simulation Results

Molecular Communication Application

# **MAP Sequence Detection**

# **Utilizing the General Definition of State**

# Something about reduced state

# **MAP Sequence Detection**

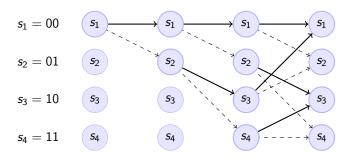
### Viterbi Setup

Maximum Likelihood sequence decoding can be formalized as

$$\begin{array}{ll}
\text{maximize} & Pr(\mathbf{y}|\mathbf{x}) \\
\text{maximize} & \prod_{i=1}^{N} Pr(y_i|\mathbf{x}) \\
\text{minimize} & \sum_{i=1}^{N} -log(Pr(y_i|\mathbf{x}))
\end{array} \tag{5}$$

## Viterbi Setup Continued

Each state change is decided by the metric  $Pr(y_i|\mathbf{x})$ . In a linear channel with length I impulse response, this metric becomes  $Pr(y_i|\mathbf{x}_{i-1}^i)$ .



Example with channel impulse response length 2 and constellation size 2.

# Incorporating Neural Net into Viterbi Decoding

#### Problem 1

Viterbi algorithm requires the distribution  $Pr(y_i|\mathbf{x}_{i-1}^i)$ .

#### ► Solution

Have a neural network learn  $Pr(y_i|\mathbf{x}_{i-1}^i)$ .

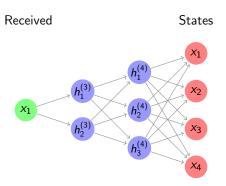
#### Problem 2

Generating training data  $Pr(y_i|\mathbf{x}_{i-1}^i)$  requires knowledge of the channel and its (current) parameters.

► Solution
Decompose  $Pr(y_i|\mathbf{x}_{i-1}^i)$  into

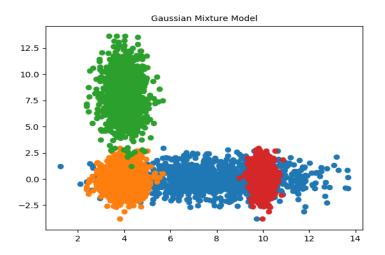
$$Pr(y_{i}|\mathbf{x}_{i-1}^{i}) = \frac{Pr(\mathbf{x}_{i-1}^{i}|y_{i})Pr(y_{i})}{Pr(\mathbf{x}_{i-1}^{i})}$$
(6)

# Metrics for $Pr(x_{i-1}^i|y_i)$



# Metrics for $Pr(y_i)$

Gaussian Mixture Model using Expectation-Maximization algorithm



The channel state perspective

The optimization framework

Extension of ViterbiNet: Reduced

Simulation Results

Molecular Communication Application

The channel state perspective

The optimization framework

Extension of ViterbiNet: Reduced

Simulation Results

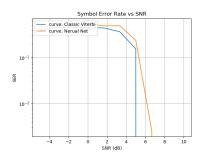
Molecular Communication Application

Conclusion

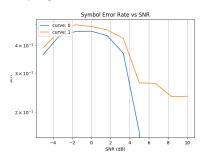
Simulation Results 18

#### **Detection Performance**

#### Without ISI



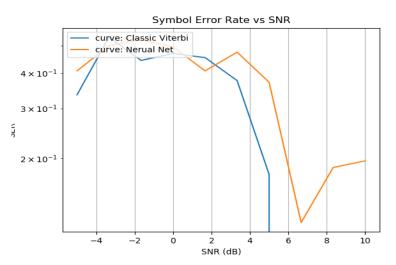
#### With ISI



Simulation Results 19

#### **Detection Performance**

Reduced Training data (100 vs. 1000 symbols)



Simulation Results 20

The channel state perspective

The optimization framework

Extension of ViterbiNet: Reduced

Simulation Results

Molecular Communication Application

The channel state perspective

The optimization framework

Extension of ViterbiNet: Reduced

Simulation Results

Molecular Communication Application

Conclusion

#### **Next Steps**

- ▶ Improve decoding performance with neural net.
- ▶ Apply to a sampled molecular communications channel.
  - Estimate matched filter
- Generate training data for molecular communications channel and test "transfer learning" to real data.

# Thank You.

# Questions or Comments?