Detection Over Unknown Channels via Machine Learning

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I. INTRODUCTION

One of the important modules in reliable recovery of data sent over a communication channel is the detection algorithm, where the transmitted signal is estimated from a noisy and corrupted version observed at the receiver. The design and analysis of this module has traditionally relied on mathematical models that describe the transmission process, signal propagation, receiver noise, and many other components of the system that affect the end-to-end signal transmission and reception. However, there are cases where tractable mathematical descriptions of the channel are elusive, either because the EM signal propagation is very complicated or when it is poorly understood. Even when the underlying channel models are known, since the channel conditions may change with time, many model-based detection algorithms rely on the estimation of the instantaneous channel state information (CSI) (i.e., channel model parameters) for detection. This estimation process typically entails overhead that decreases the data transmission rate. Moreover, the accuracy of the estimation effects the performance of the detection algorithm.

We demonstrate that, using known neural network (NN) architectures such as a recurrent neural network (RNN) [1], it is possible to train a detector without any knowledge of the underlying system model. In this scheme, the receiver goes through a training phase where a NN detector is trained using known transmission signals. We also propose a real-time sequence detector, which we call the sliding bidirectional RNN (SBRNN) detector, that detects the symbols corresponding to a data stream, as they arrive at the destination. This technique could be extended to any type of real-time estimation of data streams. We demonstrate that training the SBRNN on a diverse dataset that contains transmission sequences in different channel conditions yields a detector that is resilient to changing channel conditions and outperforms the Viterbi detector (VD) with CSI estimation error.

II. SLIDING BRNN DETECTOR PERFORMANCE

Let \( L \) be the maximum length of the BRNN. For this maximum length, during training, blocks of \( \ell \leq L \) consecutive transmissions are used for training. Note that sequences of different length could be used during training as long as all sequence lengths are smaller than or equal to \( L \). Inspired by some of the techniques used in speech recognition, we propose a dynamic programming scheme we call the sliding BRNN (SBRNN) detector. The first \( \ell \leq L \) symbols are detected using the BRNN. Then as each new symbol arrives at the destination, the position of the BRNN slides ahead by one symbol. Let the set \( \mathcal{J}_k = \{ j \mid j \leq k \land j + L > k \} \) be the set of all valid starting positions for a BRNN detector of length \( L \), such that the detector overlaps with the \( k \)th symbol. For example, if \( L = 3 \) and \( k = 4 \), then \( j = 1 \) is not in the set \( \mathcal{J}_k \) since the BRNN detector overlaps with symbol positions 1, 2, and 3, and not the symbol position 4. Let \( \hat{p}_k^{(j)} \) be the estimated PMF for the \( k \)th symbol, when the start of the sliding BRNN is on \( j \in \mathcal{J}_k \). The final PMF corresponding to the \( k \)th symbol is given by the weighted sum of the estimated PMFs for each of the relevant windows: 

\[
\hat{p}_k = \frac{1}{|\mathcal{J}_k|} \sum_{j \in \mathcal{J}_k} \hat{p}_k^{(j)}
\]

One of the main benefits of this approach is that, after the first \( L \) symbols are received and detected, as the signal corresponding to a new symbol arrives at the destination, the detector immediately estimates that symbol. The detector also updates its estimate for the previous \( L - 1 \) symbols dynamically. Therefore, this algorithm is similar to a dynamic programming algorithm.

To evaluate the performance of the SBRNN we consider the Poisson channel, which is used to model optical and molecular communication systems. Figure 1 compares the performance of the SBRNN to the VD with perfect CSI (i.e., the maximum-likelihood detector), as well as to the VDs with 2.5 and 5 percent error in CSI estimation. We see that the SBRNN outperforms VD with estimation error and comes close to the performance of the VD with perfect CSI estimation. More details can be found in [2].

REFERENCES


Fig. 1. The BER for different values of noise rates \( \eta \).