Detection Algorithms for Packet Based Wireless Networks Using Deep Learning

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***Abstract*—This paper discusses packet detection algorithms for 802.11b wireless preambles using different deep learning architectures. Two different approaches are examined, namely traditional methods and deep learning and compared by detection performance. From a traditional standpoint, preamble packet detection using correlation and its limitations are investigated. The role of deep learning is examined from three different deep learning architectures with memory, recurrent neural network (RNN), Long-short-term memory (LSTM) and Bi-directional LSTM (BLSTM). Each model's performance is evaluated against traditional detectors and each is found to outperform traditional methods considerably. BLSTM while minimizing complexity has slight superiority of evaluation metrics over RNN and LSTM. The value of using deep learning in wireless packet detection can reduce cost of hardware and increase efficiency across the industry.**

***Index Terms*—deep learning, preamble detection, wireless networks, RNN, LSTM, BLSTM**

I. Introduction

THE central research problem discussed and investigated in this paper and preceding literature review asks:

"Is there a tradeoff between traditional preamble detection techniques, against deep learning architectures in 802.11b wireless packet detection?"

For the purpose of this paper, the preamble of a wireless packet is specifically looked at for detection. Prior research has extensively explored traditional preamble detection and frame synchronization [1-3]. The preamble is a bit sequence that allows the receiver to obtain time frequency synchronization and channel estimation for each payload transmission [4]. Prior research explores deep learning being applied to wireless communication topics including channel estimation and the communication with encoders. This paper investigates, recurrent neural networks (RNN), long short-term memory (LSTM) and bi-directional LSTM (BLSTM) are evaluates performance metrics against traditional methods ensuring low complexity. The analysis assumes additive white gaussian noise (AWGN) with models robust to multipath channels. I describe in the literature review how a multivocal approach was adapted during this research, which continued throughout. Using this approach, a wide variety of viewpoints and various approaches could be analyzed and accessed. Examining detection algorithms for packet based wireless networks required setting specific search terms and alias, to gain a perspective on the ever-changing workings over time.

To determine a tradeoff between traditional and deep learning approaches to detection past analogies and methods were looked at. Specifically showing, how deep learning (DL) approaches significantly reduces the complexity and improves the performance and accuracies in comparison to traditional simple detectors. Thus, answering the question referred to in the literature review that through the use of deep learning architectures, hardware firmware can be re-configured without the need for redesign, consequently reducing costs.

Appendix A represents the literature review that looks at the initial research outlining the review and analysis of work that has been done on this topic in the past along with the intended approaches for this research paper. As the core of this research portfolio, this paper looks at prior cutting-edge methodologies in Section II, while in Section II I thoroughly go through the technical description of deep learning architectures used and their benefits to the problem. Section IV investigates the results and performs a relevant analysis. From these results, in Section V, future research proposals are introduced, and conclusions drawn.

II. Prior Work

To evaluate the impact that deep learning can have on the detection of packet based wireless networks, traditional methods of detection were evaluated against different DL architectures. The models that were implemented throughout this project were RNN, LSTM and BLSTM.

Furthermore, the trade-off between each architecture and how they outperform traditional simple detectors was evaluated with each architecture performing extensively superior to traditional methods, minimizing model complexity [5].

A. Traditional Wireless Packet Detection

Traditionally, wireless packet detection consists of calculating the correlation of possible packet preamble sequences and the received signal. A threshold value modified essentially given the noise floor is used to detect the signal efficiently. The improved composite pseudo noise correlation (ICMP) method of detection correlates preconceived preamble sequences against received signals [6]. The correlation of both, shows peaks at specific positions where preamble sequences are detected, while if no peaks occur the correlation value is commensurate to the length of the preamble sequence.

Traditional method detection algorithms are used in many communication systems [7-9]. However, with these approaches to achieve robust,scalable results the algorithm requires some feature engineering. By taking a deep learning approach, this project will evaluate how these problems can be overcome to produce more robust, low complexity algorithms outlined in [10-18].

B. Deep Learning Approaches

DL techniques are rapidly becoming widely used in the wireless communications domain in various areas [18-19]. Many applications have engineered architectures for specific classification, [20] and regression, [21] problems to significantly improve robustness, scalability and design. Thus, resulting in a better performing application.

Several DL approaches have been investigated to determine sequence classifications. Research in [10], outlines DL architectures using the Poisson channel model applied to optical and molecular systems. A Sliding bidirectional recurrent neural network (SBRNN) technique is trained to estimate the data in real-time as the signal stream arrives at the receiver. Similarities between molecular and wireless communication systems is shown in Fig. 1. The approach taken here is different from prior works since it is assumed that the mathematical models for the communication are Poisson channels.

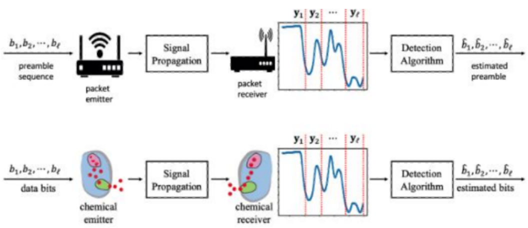


Fig. 1. Similarity between molecular communication using a Poisson channel model and wireless communication using an additive white gaussian noise channjel

In further research, [22] investigates the use of convolutional neural networks (CNN) for preamble detection and Time of Arrival (TOA) estimation without the need of knowing the transmit waveform. The specific waveforms given, are classified against received waveforms with the addition of AWGN, due to the multipath propagation effect. Through the use of a CNN, trained on both synthetic and real measured data shows the prediction accuracy in comparison to traditional approaches improved by three times, while carrying the same computational complexity.

III. Technical Description

This paper builds upon the traditional correlation methods of detection, finding the tradeoff between DL approaches and traditional simple detectors. The theory implemented throughout this paper and architectures researched are outlined here.

A. Deep Neural Network Overview

With emerging DL technologies, and their ability to classify and predict specific outcomes, models are being produced in industry at scale. As outlined above, an 802.11b wireless packet preamble is a pseudorandom sequence, which will be used for detection. Thus, different artificial NN architectures were implemented to utilize their memorizing capacities for long range preamble sequences, namely RNN, LSTM and BLSTM. Fig. 2, outlines the general architecture of a neural network, where the input vectors are $x_1, x_2, ..., x_n$. W represents the weights connection to the next layer, bias is represented by b_k and y_k is the final output after being passed through an activation function.

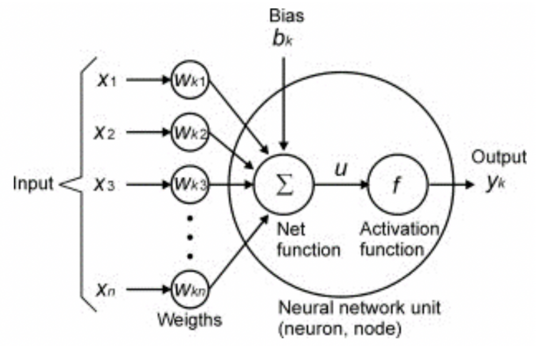


Fig. 2. General structure of a Neurel Network , showing weights conecting the input vectors to the next layer then being passed to an activation function to produce an output [23]

B. Data Acquisition

Prior research substantiates the belief that an 802.11b wireless packet uses direct sequence spread spectrum (DSSS), to reduce overall signal interference. Packet bits are modulated using pseudorandom spreading sequences, to provide signal privacy against multiple packets using the same resource. For the purpose of this paper maximum length sequences are used as the spreading sequence due to excellent auto correlation abilities for large sequences.

M-sequences are generated using linear feedback shift registers (LFSR) structures. Galois field architecture is applied in the generation of sequences. (1), denotes an L_{th} order polynomial in GF(2) taking only binary values. L represents delay elements, where $g_0, g_1, ..., g_L$ represent the coefficients of the generator polynomial [27].

$$g(x) = g_0 + g_1 x + g_2 x^2 + \cdots + g_{L-1} x^{L-1} + g_L x^L \pmod 2 \quad (1)$$

Comprehensive simulations of three datasets generated using contrasting elements of noise and channels are evaluated.

1) Binary Symmetric Channel (BSC): Both channel input and output are binary, with error probability based on receiving an incorrect bit. Each data point, takes an m-sequence and is passed through a BSC model for a given error probability, resulting in a randomly flipped sequence.

2) Additive White Gaussian Noise (AWGN) Channel: This dataset consists of m-sequence datapoints over an AWGN channel, whose amplitude is gaussian distributed. Various signal to noise ratios (SNR) values in the range of -15 to 10 in steps of 5 are simulated.

3) Multipath Channels: Multipath channels arrive at the receiver with multiple different strengths and phase angles of the same signal causing many variations. Each datapoint generated consists of 100 random normalized channels convolved with the current LFSR sequence of each packet, with added AWGN with a SNR of -5 dB.

C. Recurrent Neural Network

As referred to in the literature review an RNN is a generalization of a feed forward neural network that has an internal memory [10]. Thus, when making a decision the model considers the input and output that it has learned previously. [11], takes the approach defined by

$$h_t = j_h\left(x_t, h_{t-1}\right) = \phi_h\left(W^\tau h_{t-1} + U^T x_t\right) \tag{2}$$

$$y_t = j_0\left(h_t, x_t\right) = \phi_o\left(V^T h_t\right) \tag{3}$$

Where W, U and V are the transition, input and out matrices ϕ_h and ϕ_o are element wise nonlinear functions. While having an input x_t, an output y_t , and hidden state h_t.

The received signal was first reshaped to a three-dimensional array, with X number of samples, one time step and 38 features. The three-dimensional input sequence then goes through the model with 38 neurons. To reduce the overall complexity of the model, a recurrent dropout rate of 0.2 is introduced on the simple RNN layer, with the addition of two dense layers gradually reducing the kernel size. Table one, shows the final model summary. The sigmoid activation function was also used [24]. ReLU activation was considered here, however as outlined in the literature review RNNs are unable to process very long sequences if used. The resulting model yielded a resounding performance accuracy evaluated against traditional detectors, seen in Section IV.

However, with RNN's the vanishing gradient and exploding gradient problem must be addressed, resulting in a non-robust model using multipath data.

TABLE I
RNN MODEL SUMMARY

Type	Output Shape	Parameters
Simple RNN Layer	(None,1,38)	2926
Global Max Pooling	(None,38)	0
Dense Layer	(None,16)	624
Dropout	(None,16)	0
Dense Layer	(None,1)	17

D. Long Short-Term Memory

RNNs come with a degree of complications. LSTM networks [12], a modified version of RNN, resolves the above vanishing gradient problem resulting in a more robust, low complexity model for the purpose of this project. Fig. 3, illustrates a general LSTM architecture an added output gate, forget gate, input gate and memory cell which in turn stores information over long periods of time. The added gates of LSTM are used to take the model offline, delete sequences and neglect incoming activations [15]. Through this, working with long preamble sequences illustrates a straightforward process.

The input gate, forget gate, output gate and cell state vector are outlined as $i(t)$, $f(t)$, $o(t)$, $c(t)$ while computed by standard means highlighted in the aforementioned literature review.

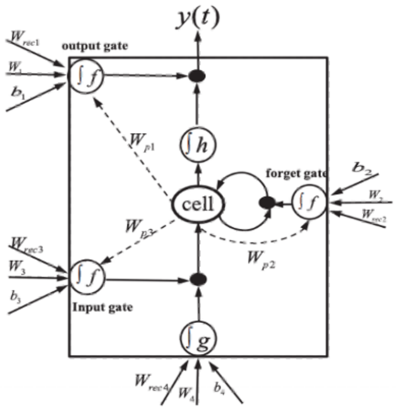


Fig. 3. General Structure of LSTM model. The LSTM cell shows the nput gate, forget gate, output gate. The LSTM use both sigmoid and tanh activation functions to produce outputs

The semantic representation of the preamble is shown by $x_t$when the input preamble sequence is the last preamble sequence y_t [16].

As illustrated in the RNN approach, a low complexity solution is paramount. The received signal is reshaped into a three-dimensional array the same as the previous approach and passed to a two-layer LSTM model using 38 neurons, with one dense layer using the sigmoid activation function. Table two shows the final model summary.

TABLE II
LSTM MODEL SUMMARY

Type	Output Shape	Parameters
LSTM Layer	(None,1,38)	11704
LSTM Layer	(None,38)	11704
Dense Layer	(None,1)	39

However, the LSTM architecture can be re-engineered to understand the context of the preamble and preserve information from both the past and future by running input two ways. Using a BLSTM this can be achieved.

E. Bidirectional Long Short-Term Memory

BLSTM models hold a significant advantage over previous architectures, as preamble sequences can be preserved. A BLSTM runs inputs in two ways, one from the future and one from the past. In this model, input is presented in forward and backward states to two separate LSTM networks, that are both connected to the same output layer [17]. By preserving information from the future and using two hidden states $\overrightarrow{h_t}$ and $\overleftarrow{h_t}$ respectively, we can combine both layers and successfully preserve preamble information from both the past and future to compute the output sequence y_t shown in Fig. 4

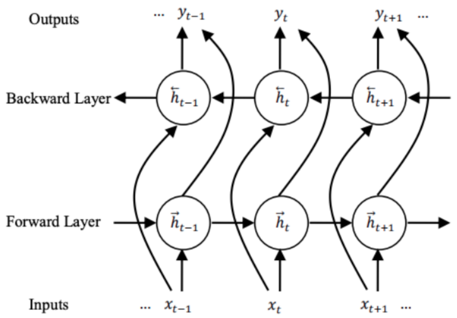


Fig. 4. General Structure of BLSTM model. The bottom LSTM layers shows the forward feature, while the top LSTM feature is used for backward feature. Both LSTM layers connect to an activation function to produce outputs

Likewise, in RNN and LSTM model data preprocessing, the received signal is reshaped and fed to the model. In this case, the final models consist of two initial Bidirectional LSTM layers with 38 neurons followed by a global pooling layer, reducing dimensionality and complexity. As used in the LSTM model, a dense layer is used to reduce the kernel size to 16, followed by a dropout rate of 0.2. The features are then extracted with a final dense layer using the sigmoid activation function. The final model summary can be seen in table 3.

By using this model, the robustness and resilience of the model was maximized to ensure significantly improved results over the LSTM and RNN models shown in Section IV.

TABLE III
BLSTM MODEL SUMMARY

Type	Output Shape	Parameters
Bidirectional LSTM Layer	(None,1,62)	15624
Bidirectional LSTM Layer	(None,62)	23312
Global Max Pooling	(None,62)	0
Dense Layer	(None,16)	1008
Dropout 0.2	(None,16)	0
Dense Layer	(None,1)	17

F. Model Training

A training and test dataset were derived from each dataset before training commenced. The datasets generated in part B, contain an input x and the corresponding label y. The input x represents the received signal sequence. The label y represents the binary representation of signal detection. The loss function used to evaluate each model was binary cross-entropy.

Where y is the label, with 1 representing a dected preamble sequence, otherwise 0 and $p(y)$ evaluating to the predicted probability of the sequence being a detected preamble for all data points. The optimizer used across all final models is the efficient Adam optimizer, however the SGB optimizer was tested yielding poorly results. The model is fit over multiple epochs, with a reduced learning rate callback, with a factor of 0.1. Resulting in a model learning rate being reduced based on a patience value of 2.

The testing stage consists of the unseen testing data being evaluated with the trained model. It is ensured that the model uses data it has not encountered previously. The output of each models represents a detected preamble or otherwise.

G. Evaluation Metrics

The academic community has extensively explored evaluation metrics to determine the effectiveness and performance of DL models. In this paper, Neyman Pearson Lemma curevs are used to dissect the performance and tradeoff between traditional and DL approaches of detection of the final models. False alarm rates are plotted against missed detection rates to outline the performance of the different methods used [24]. Receiver Operating Characteristic (ROC) curves are used to compare models for each dataset by plotting the true positive rate against false positive rate for varying thresholds [25]. Area Under Curve (AUC) curves are also evaluated to aggregate the measurement of performance across all possible thresholds. Precision and recall of models are also considered for comparison of model performance.

IV. Experimental Results and Analysis

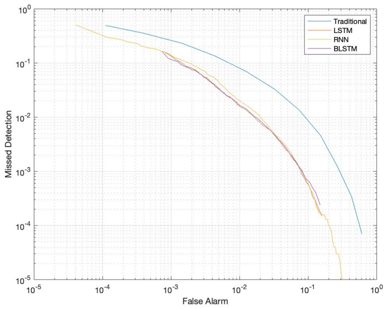
A. Binary Symmetric Channel Data

Each DL architecture's detection performance is evaluated using the aforementioned evaluation metrics. Fig. 5 (a) compares traditional methods and DL methods of detection using Neyman-Pearson curves to determine the highest performance. If a packet is detected, where the prediction is wrong the error represents a false alam, since we mistakenly detected the wrong packet received. This is shown on the x axis. In contrast to not detecting a packet, when it is a packet represents missed detection shown on the y axis. With a probability threshold of, λ as it decreases or increases the curve becomes smaller or larger.

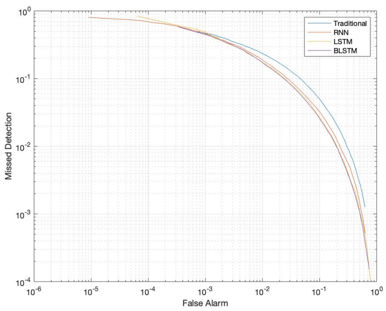
TABLE IV
Performance Evaluation of Models of BSC Data

	RNN	LSTM	BLSTM
Parameters	2,482	16,153	39,961
Accuracy	0.98	0.98	0.98
Precision	0.97	0.98	0.98
Recall	0.98	0.98	0.97
AUC	0.99	0.99	0.99

In (a) the trained model curves are significantly inside the traditional method resulting in the level of detection being higher. The closer the models NP curve comes to the traditional curve shows that the level of detection is reducing. It can be seen in Table. IV that the RNN model has the highest performance with a lower rate of trainable parameters ensuring low complexity. It specifies when a packet is correctly detected, the model is correct 96% of the time, while also indicating a correct detection of 98% of packets.



(a) BSC Data



(b) AWGN Data

Fig. 5. Neyman Pearson Curves of Traditional Detection Methods Vs DL models using BSC and AWGN Data

B. Additive White Gaussian Noise Data

TABLE V
PERFORMANCE EVALUATION OF MODELS OF AWGN DATA

	RNN	LSTM	BLSTM
Parameters	2,482	15,656	39,961
Accuracy	0.94	0.94	0.94
Precision	0.95	0.94	0.95
Recall	0.92	0.94	0.94
AUC	0.98	0.98	0.98

The findings here, surmise the effectiveness of performance metrics of models. Initially, substandard performance results initiated that traditional approaches outperformed all DL models substantially. However, the generation of additional data rapidly increased performance metrics to outperform traditional approaches. As mentioned in Section III, varying SNR dB values ranging from -15 dB to 10 dB were evaluated. As data encoding SNR is 0 dB, -5 dB SNR is analyzed. Fig. 5 (b), as outlined above outlines NP curves to compare different methods. In contrast to Fig. 5 (a) the margin of detection has reduced, however this is expected as the level of noise has increased. Table. V shows that the BLSTM model detection performance is high, however relatively close to the RNN with 10x lower training parameters.

However, as the value of SNR dB increases the less noise is in the received signal, resulting in higher performing detection models. In contrast, as the value of SNR dB decreases additional noise has a relatively small effect on the performance of each model. Table four, strengthens this observation. Evidently, through each value of SNR dB examined the DL models substantially outperform traditional methods while ensuring low complexities discussed in part (d) of this section.

TABLE VI
LSTM MODELS FOR VARYING SNR DB SUMMARY

	Precision	Recall
10 SNR dB	0.97	0.99
-10 SNR dB	0.69	0.71
0 SNR dB	0.99	0.99

C. Multipath Data

TABLE VII
PERFORMANCE EVALUATION OF MODELS OF MULTIPATH DATA

	RNN	LSTM	BLSTM
Parameters	3,567	23,447	59,617
Accuracy	0.95	0.95	0.94
Precision	0.96	0.97	0.97
Recall	0.94	0.94	0.92
AUC	0.94	0.95	0.94

Fig. 6 looks at the NP curves to compare traditional methods and DL methods on multipath data. Interestingly, it can be seen that the margin between traditional and DL approaches is large, showing that all DL models increase the level of detection even through multipath data with added AWGN noise. These results show how far DL models can bring the detection of packets, thus, reducing costs as hardware will not have to be redesigned with the updating of firmware serving sufficient. The scalability and robustness of models outweighs traditional methods while keeping the same complexity.

V. CONCLUSION AND FUTURE WORK

This paper illustrates the power of DL architectures and when applied correctly can have a major impact on packet detection and the wireless communications industry. Three neural network architectures with memory were applied to

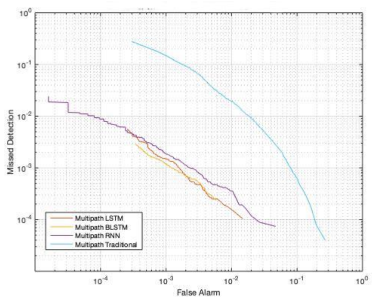


Fig. 6. Neyman Pearson Curves of Traditional Detection Methods Vs DL models using Multipath Channel Data

three separate datasets in this paper to find the tradeoff between DL approaches and traditional simple packet detectors. The models implemented outperform traditional methods immensely in accuracy, precision and recall while ensuring low complexity.

The BLSTM architecture is found to perform significantly outweigh traditional approaches for low values of SNR dB and multipath channels.

Future work includes running the model on sequential input and performing anomaly detection within each packet to determine its relevance.

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