Ollscoil Chathair
Bhaile Átha Cliath
Dublin City University

School of Electronic Engineering

Detection Algorithms for Packet based Wireless Networks using Deep Learning

Literature Survey

Niall Lyons
ID Number: 13493628

March 2020

MEng in Electronic and Computer Engineering

Supervised by

Dr. Kevin McGuinness

Declaration

I hereby declare that, except where otherwise indicated, this document is entirely my own work and has not been submitted in whole or in part to any other university.

Signed: Niall Lyons Date: 09/04/20

Detection Algorithms for Packet Based Wireless Networks Using Deep Learning

Niall Lyons

***Abstract*—In this paper, detection algorithms for packet based wireless networks using deep learning will be discussed. This will be examined using two different approaches, namely traditional methods of packet detection and the application of deep learning models to detect wireless packets. From a traditional standpoint, it is first looked at preamble packet detection using correlation and the limitations that it has. The role of deep learning is then examined from three different deep learning architectures, recurrent neural network (RNN), Long short-term memory (LSTM) and Bi-directional LSTM (BLSTM). Each of the architectures are then assessed in terms of performance and precision and evaluated against traditional methods of detection. It is found that the BLSTM neural network architecture will perform at a higher level to the LSTM and RNN while being compared to traditional methods. The value of using deep learning in wireless packet detection is found to reduce cost of hardware and efficiency across industry.et**

***Index Terms*— deep learning, preamble detection, wireless networks, communication systems**

I. Introduction

PACKETIZED communication is quickly becoming the standard throughout wireless systems used in industry today. As stated by IEEE standards for local, metropolitan and personal area networks and several other communication standards. In this form of communication, packets are random and unknown to the receiver. For the purpose of this paper, the preamble of the packet will specifically be looked at. The preamble is a section of data prefixed for each payload transmission at the head of the wireless packet to facilitate the process of synchronization. Figure 1 shows the typical packet format showing the exact starting time of the payload. Therefore, throughput this paper preamble detection in wireless based networks is addressed.

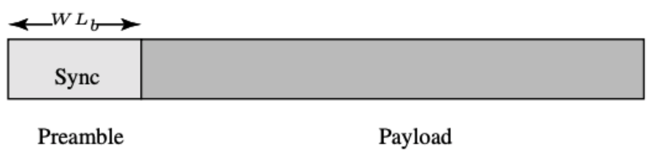


Fig. 1. Packet Format

When researching this topic, a multivocal approach was adopted, meaning that both peer reviewed and non-peer-reviewed artefacts were included. With this approach, a wide range of perspectives and different methods could be addressed and evaluated. Examining detection algorithms for packet based wireless networks using deep learning is an expensive undertaking, meaning specific search terms and alias were considered. Through a preliminary examination of literature, it was found that at the present time there are few published documents relating to this topic that consider deep learning. Therefore, workings over time were considered genuine to gain a perspective on methods introduced over time.

To thoroughly evaluate how deep learning methodologies can benefit the detection of wireless networks based on the packet's preamble, past analogies must be looked at. Specifically, how deep learning can change the problems, accuracies and dramatically improve the preconceived state of the art methodologies of the past. In particular, with the use of deep learning, hardware can be re-configured without the need for redesign, thus reducing cost. Along with this, how the robustness and low complexity detection of deep learning models outweighs previous traditional detection algorithms. However, new techniques must be extensively tested to ensure detection algorithms can perform under changing noisy channel conditions without underlying knowledge of channel models.

Traditional methods of detection have changed overtime; however, the deep learning approach has branched out to different types of deep learning methodologies. In this paper, recurrent neural networks (RNN), long short-term memory (LSTM) and bi-directional LSTM (BLSTM) will be evaluated against traditional methods. Identifying the discrepancies between traditional and deep learning architectures will eliminate the need for feature engineering and unnecessary costs and utilize the best deep learning approach to deliver high quality results.

Three different types of architectures with memory will be discussed and tested to determine the best approach to detect wireless packets, and show it is possible to train detectors that perform well, without any knowledge of underlying channel models. The accuracy of the BLSTM model will be evaluated against an RNN model and traditional digital signal processing methods, for comparison to determine the best possible method. These models will be evaluated using IEEE 802.11 [10] standard compliant data where the model and channels are unknown. The aim is to find the trade-off between BLSTM and RNN architectures and evaluate how they outperform traditional simple detectors.

The rest of the paper is organized as follows. In section II, traditional models of preamble detection are described, while the above deep learning architectures are analyzed in relation to prior work. In section III, prior work to the project problem is reviewed and how these workings can assist this particular topic. The conclusion follows in section V.

II. Review and analysis of prior work

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

Furthermore, the trade-off between BLSTM and RNN architectures and how they outperform traditional simple detectors will be evaluated.

A. Traditional Methods

In [1], the performance bounds on detecting a preamble embedded at the beginning of every packet for communication over an additive white Gaussian noise channel are derived. Correlation based detection is used to detect the preamble with an extensive performance analysis undertaken. Here the probability of successful preamble detection is given by

$$P(success) = 1 - P(wrong) - P(miss) \quad (1)$$

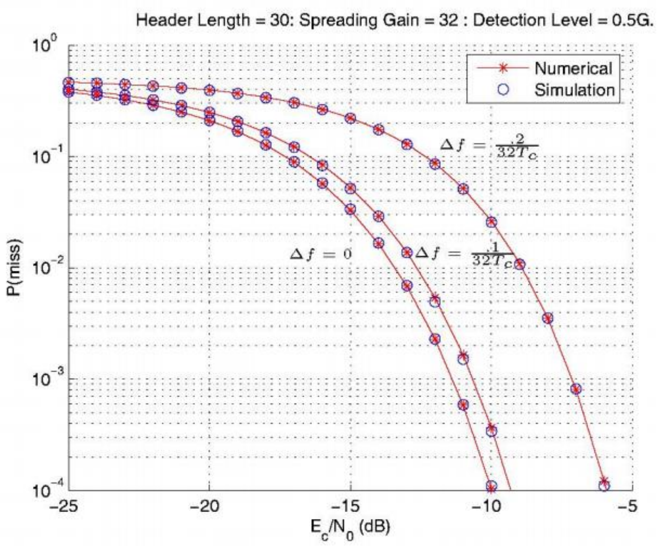
With the probability of miss given by

$$P(miss) = P(Re\ \eta_{i0} < G) = P\left(\sum_{i=0}^{W-1} \lambda_i\ |Z_i|^2 < 2G\right) \quad (2)$$

And the probability of wrong given by

$$\begin{aligned} P(wrong) &= \sum_{i=1}^{S} P(wrong|i)P(i_0 = i) \quad (3) \\ &\leq \sum_{i=1}^{S}\sum_{k=1}^{i-1} P(Re\ \eta_k\ \geq G|i)P(i_0 = i) \quad (4) \\ &\cong \left(\frac{1}{\lambda} - 1\right) P(Re\ \eta_1\ \geq G) \quad (5) \end{aligned}$$

where $\frac{1}{\lambda} - 1$ represents the wireless packet communication traffic intensity. The overall performance of this method is outlined in figure 2 and figure 3.



Fig, 2. Probability of missing a packet using cross correlation for different SNR and offset values

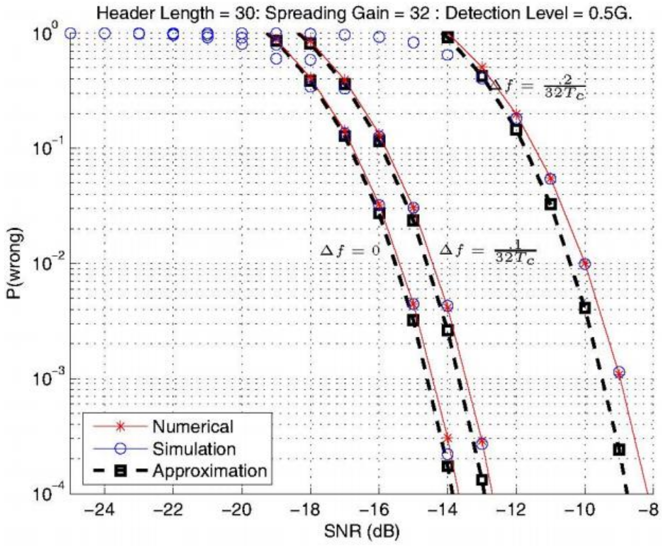


Fig. 3. Probability of erroneous packet detection using cross correlation for different SNR and offset values

Figure 2 shows the probability of packet loss for different signal noise ratio (SNR) and frequency offset values and reduces the probability of intercarrier inference. Thus, reducing the signal-to-noise ratio (SNR). Frequency offset values are calculated to reduce the interference between transmitter and receiver. Figure 3 shows the probability of erroneous packet detection.

However, with this approach to achieve these results the algorithm requires some feature engineering as the presence of frequency offset rotates the signal and degrades the performance. 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 [2-9].

B. Recurrent Neural Network

To utilize the power of deep learning and overcome the problems above, as outlined in [3], an RNN is a generalization of a feed forward neural network that has an internal memory. Neural network (NN) architectures with memory are used over alternative NN architectures as preamble sequences are stored in memory to detect wireless packets. Therefore, when making a decision, it considers the current input and the output that it has learned previously. Taking the approach of an RNN in [4], it is defined by

$$h_t = j_h(x_{t,} h_{t-1}) = \phi_h(W^T h_{t-1} + U^T x_t) \quad (6)$$

$$y_t = j_o(h_{t,} x_t) = \phi_o(V^T h_t) \quad (7)$$

Where W, U and V are the transition, input and out matrices and ϕ_h and ϕ_o are element wise nonlinear functions. While having an input $x_{t,}$, an output $y_{t,}$ and hidden state $h_{t,}$.

However, the RNN methodology applied to the preamble detection has its disadvantages. RNNs are unable to process very long sequences if they use ReLU as an activation function. Resulting in a non-efficient and costing model. Moreover, the vanishing gradient and exploding gradient problem will have a sufficient impact on the performance of the model. [5] Thus, bringing its overall value and robustness of low quality.

C. Long Short-Term Memory

As outlined above, RNNs come with a degree of complications. LSTM networks [6], a modified version of RNN, resolves the above vanishing gradient problem developing a more robust, low complexity model for the purpose of this project. The architecture of an LSTM is shown in figure 5. This figure shows 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. [8] An advantage of using this type of architecture in this project, as working with lengthened CDMA preamble sequences is straightforward.

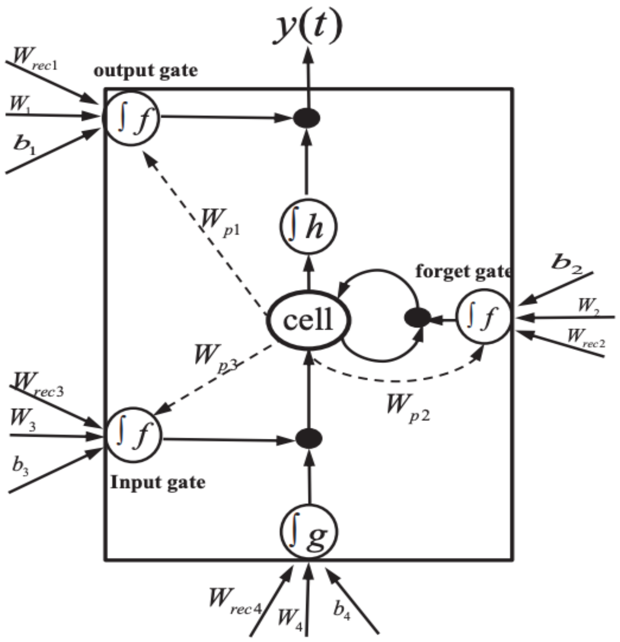


Fig. 5. LSTM Architecture

The output gate, forget gate, input gate and cell state vector are outlined as $o(t), f(t), i(t)$ and $c(t)$ are computed as follows

$$i(t) = \sigma\left(W_3 x(t) + W_{rec3} y(t-1) + W_{p3} c(t-1)\right) \quad (8)$$

$$f(t) = \sigma\left(W_2 x(t) + W_{rec2} y(t-1) + W_{p2} c(t-1)\right) \quad (9)$$

$$o(t) = \sigma\left(W_1 x(t) + W_{rec1} y(t-1) + W_{p1} c(t-1)\right) \quad (10)$$

$$l(t) = tanh\left(W_4 x(t) + W_{rec4} y(t-1)\right) \quad (11)$$

$$c(t) = f(t)c(t-1) + i(t)l(t) \quad (12)$$

$$y(t) = \tanh\left(c(t)\right) o(t) \quad (13)$$

where W_i and W_{reci} (i=1,2,3,4) are input connections and recurrent connections of output gate, forget gate, input gate and cell. W_{pi} (i=1,2,3) represents peephole connections. Activation functions $tanh(.)$ and $\sigma(.)$ are used. $\sigma(.)$ represents the sigmoid function. The semantic representation of the preamble is shown by x_t, when the input preamble sequence is the last preamble sequence y_t. [7]

The performance and robustness of LSTM over RNN will be looked at to test for tradeoff between detected probability and false alarm probability using a receiver operating characteristic (ROC) curve to display the relationship.

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 Bi-directional LSTM (BLSTM) this can be achieved.

D. Bi-directional Long Short-Term Memory

As outlined above we can preserve preamble data using a BLSTM. The 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. [9] By preserving information from the future and using two hidden states $\overleftarrow{h}$, $\overrightarrow{h}$ respectively, we can combine $\overleftarrow{h}$ and $\overrightarrow{h}$ to successfully preserve preamble information from both the past and future and compute the output sequence y shown in figure 6.

$$\overrightarrow{h}_t = \mathcal{H}\left(W_{x\overrightarrow{h}} x_t + W_{\overrightarrow{h}\overrightarrow{h}} \overrightarrow{h}_{t-1} + b_{\overrightarrow{h}}\right) \quad (14)$$

$$\overleftarrow{h}_t = \mathcal{H}\left(W_{x\overleftarrow{h}} x_t + W_{\overleftarrow{h}\overleftarrow{h}} \overleftarrow{h}_{t+1} + b_{\overleftarrow{h}}\right) \quad (15)$$

$$y_t = W_{\overrightarrow{h}y} \overrightarrow{h}_t + W_{\overleftarrow{h}y} \overleftarrow{h}_t + b_y \quad (16)$$

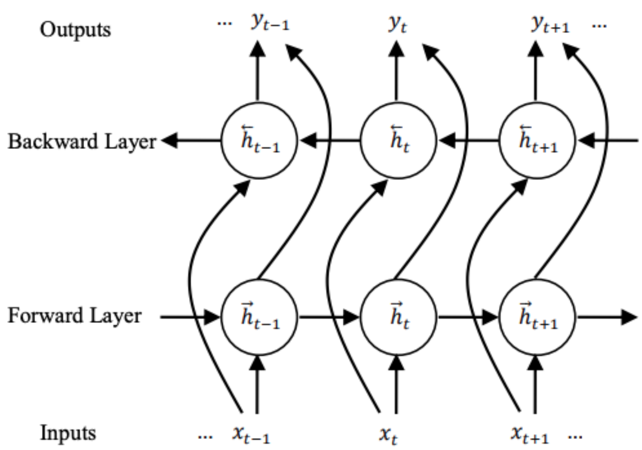


Fig. 6. BLSTM Architecture

By using this model, the robustness and resilience of the system will be maximized to ensure significantly improved results over the LSTM and RNN models. The tradeoff between each model in relation to traditional methods outlined in II part A, will be examined to determine the most robust model and by how much it outperforms traditional methods of wireless packet detection.

III. Review of Prior Work to the Project Problem

Part of the challenge when faced with a problem is to determine whether or not deep learning needs to be applied, and what advantages it will have over a traditional method. In this project, the aim is to determine what advantages different deep learning models will have to traditional approaches in preamble by preamble detection in wireless based networks. The main problems being addressed by this project is by developing deep learning models, hardware can be re-configured without need for re-design, thus reducing cost. The robustness of these models is key to show it is possible to train detectors that perform well without any knowledge of underlying channel models.

In [3], many different NN detectors are directly trained using measurement data from experiments. These NN architectures use a Poisson channel model to be used in optical and molecular communication systems. Sliding bidirectional recurrent neural networks (SBRNN) are trained. After training, the detector estimates the data in real-time as the signal stream arrives at the receiver. Similarities between molecular and wireless communication systems is shown in figure 7. The approach taken here is different from prior works since it is assumed that the mathematical models for the communication are Poisson channels.

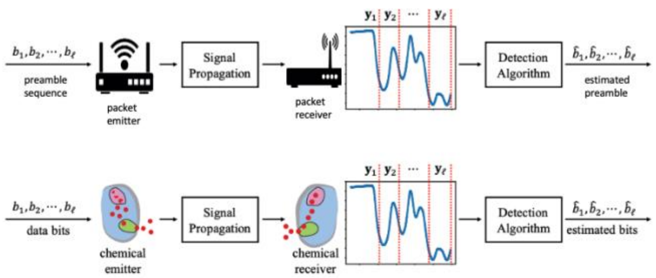


Fig. 7 Similarity between molecular and wireless communication systems

This project is a state-of-the-art deep learning approach to the detection problem in wireless communication systems. Different NN detection architectures will be trained using IEEE 802.11 standard generated preamble data. [10] The models outlined in section II, use preamble data with a gaussian channel model used in wireless communication systems. This model is used to compare the performance against traditional methods of detection. Through this comparison, the best model can be evaluated and tested thoroughly to ensure it is robust, accurate, resilient and fit for purpose.

The proposed solution aims to be show how deep learning can replace and outperform traditional wireless packet detectors. Each architecture's will visually show the progression from traditional methods through RNN and different types of RNN, LSTM and BLSTM.

IV. Conclusions

Packet based wireless detection algorithms in communication systems are complex and in earlier work rely on known underlying channel models. The challenges involved in developing an algorithm that can detect wireless packets without any known underlying channel models involves deciding what specific deep learning models we want to use and how their performance and architectures will benefit the problem we are trying to solve.

We have therefore examined three different models in depth, to evaluate the best possible method to solve the given problem. This research suggests that a BLSTM at the present time, will outweigh the RNN and LSTM models in terms of precision and accuracy. However, it can be said that computationally this could be expensive with the LSTM model the better option.

Researchers and engineers are emerging with new and improved deep learning models at a vast pace. This research indicates that deep learning is the future of detection algorithms in packet based wireless networks, although traditional methods work and work efficiently. The reduction of costs and re-configuration of hardware without redesign will evidently be used in industry going forward.

References

[1] S. Nagaraj, S. Khan, C. Schlegel, and M. Burnashev, "On preamble detection in packet-based wireless networks," in *IEEE International Symposium on Spread Spectrum Techniques and Applications*, 2006, pp. 476–480, doi: 10.1109/ISSSTA.2006.311817.

[2] Y. Lecun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553. Nature Publishing Group, pp. 436–444, May 27, 2015, doi: 10.1038/nature14539.

[3] N. Farsad and A. Goldsmith, "Neural Network Detection of Data Sequences in Communication Systems."

[4] R. Pascanu, C. Gulcehre, K. Cho, and Y. Bengio, "How to Construct Deep Recurrent Neural Networks."

[5] S. Squartini, A. Hussain, and F. Piazza, "Preprocessing based solution for the vanishing gradient problem in recurrent neural networks," in *Proceedings - IEEE International Symposium on Circuits and Systems*, 2003, vol. 5, doi: 10.1109/iscas.2003.1206412.

[6] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," *Neural Comput.*, vol. 9, no. 8, pp. 1735–1780, Nov. 1997, doi: 10.1162/neco.1997.9.8.1735.

[7] Y. Lu, Y. Shi, G. Jia, and J. Yang, "A new method for semantic consistency verification of aviation radiotelephony communication based on LSTM-RNN," in *International Conference on Digital Signal Processing, DSP*, Jul. 2016, vol. 0, pp. 422–426, doi: 10.1109/ICDSP.2016.7868592.

[8] A. Graves, N. Beringer, and J. Schmidhuber, "Rapid Retraining on Speech Data with LSTM Recurrent Networks Instituto Dalle Molle di studi sull' intelligenza artificiale Galleria 2 CH-6900 Manno, Switzerland Rapid Retraining on Speech Data with LSTM Recurrent Networks," 2005.

[9] A. Graves and J. Schmidhuber, "Framewise Phoneme Classification with Bidirectional LSTM Networks."

[10] The Institute of Electrical and Electronics Engineers, "IEEE Standard for Information technology--Telecommunications and information exchange between systems LAN and MAN--Specific requirements - Part 11: Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications, IEEE Std 802.11-2016," *IEEE Std 802.11-2016 (Revision IEEE Std 802.11-2012)*, vol. 2016, pp. 1–3534, 2016, doi: 10.1109/IEEESTD.2016.7786995.