DESIGN OF PHYSICAL RANDOM ACCESS CHANNEL FOR NEW RADIO (5G)

Author
Naresh Modina
ID 852279

Supervisor:
Prof. Mourizio Magarini

Tutor:
Riccardo Ferrari

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Abstract

THIS work focuses on the design of Physical Random Access Channel (PRACH) for New Radio (5G) and implementing a simulator in matlab. PRACH is a physical uplink channel responsible for random access procedure. I implemented a simulator which comprises of a transmitter and receiver. The design of PRACH must follow 3GPP specification, so that it would be compatible with the industry requirements. Our initial idea is to adapt the existing LTE simulator (which was designed for PRACH in LTE) to 5G standard. The adaptation part must include introduction of numerology in the frame structure and support for OFDMA as these are some of the noticeable changes in the transition from LTE to NR. The transmitter part has been successfully adapted, so is the receiver but with a small issue. After using the same detection algorithm that was used for LTE, we realized that there is degradation in the performance due to detection of false peak (extra peak that is being detected along with the original peak).

The main challenge was to design an algorithm which can avoid detecting or eliminate this false peak, which is appearing so randomly. We believed a conventional approach to this problem is not suitable. The nature of the issue forced us to try machine learning algorithms as it can learn the behaviour of the issue based on the training sequence. There are very good algorithms in literature for this specific issue, so we preferred to use classification algorithms to differentiate the false peak with the original peak (preamble). The idea is to collect the data (mean and
variance of the power delay profile of the received signal) using the existing receiver. And then use this data to predict the response of the received signal. After testing several algorithms like $k$-NN, Naïve Bayes, DTC on the collected data using the machine learning tool in matlab, we believed this idea would work. After employing this technique, we observed improvement in the performance. But it was still not sufficient, then we decided to use a hybrid method which combines DTC and Naïve Bayes to reach the performance target. This solved the problem of detecting two peaks and in doing so, it improved the performance of the receiver.
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CHAPTER 1

Introduction

This chapter describes the structure of this work and will provide an introduction to 5G and machine learning is well.

1.1 Introduction to New Radio

New Radio (NR) is the next generation wireless technology for mobile and wireless communication beyond 2020. The very fundamental advantage of New Radio is the flexibility as it supports different services [27]. There are different scenarios where 5G will play a crucial role, For example massive machine type communication, ultra reliable low latency communication, see [19] for details. It is evident to see that NR has immense potential which could push the telecommunication industry to new heights and show its diversity.
Chapter 1. Introduction

Figure 1.1: New Radio use case scenarios

Of course, it comes at the expense of more complex architecture. Given the trend of electronic industry, Next Generation Wireless Systems (NGWS) would require new frequency spectrum as the current frequency spectrum used in LTE is crowded. As the name (New Radio) suggests, a new radio frequency is being explored in order to satisfy the bandwidth requirements in 5G. The new spectrum in context is millimeter wave (mm-wave) frequencies [20]. Along with mm-waves there are multiple technologies which enables the next generation wireless systems. They are

- mm-waves
- small cell
- massive MIMO
- beamforming

Millimeter waves

The most important resource in telecommunication is frequency band. It is a very scarce quantity. As of now the available frequency is already being used to full extent, in order to enable different use case scenarios, more frequency is needed. In fact much larger than the available frequency spectrum. This leads to a higher frequency spectrum which is
1.1. Introduction to New Radio

in mm waves range [20]. It is promising as it enables a whole new frequency band which is essential for 5G. But, the main disadvantage with mm waves is the absorption [16]. This will reduce the coverage. Covering the large area in the existing cell may not be possible, instead small cells could be employed to efficiently use these frequency bands. This leads to the concept of small cell [17].

Figure 1.2: Coverage for various frequency ranges

Small cell

As it has been have mentioned above, if we were to use mm waves we must build a network which is efficient in using them. Here comes small cell, an idea which might pave the way to enable usage of mm waves. Of course, having small cell alone is not sufficient we must make sure that the waves are not being absorbed by plants and other things to which mm-waves are sensitive. So, directing the beams to (UE) would be a good idea, this is possible with beamforming. Beamforming will reduce interference is well, as it has better main lobe and significantly lower side lobes.
Chapter 1. Introduction

Beamforming

One idea to reduce interference among congested areas and avoid absorption is to use beamforming to direct the signal in specific direction [21]. As an additional benefit when we use beamforming we will have better SNR compared to normal case. This is definitely a benefit considering the channel behaviour in urban environments. There are different types in beamforming, Analog, digital, and hybrid(a mixture of analog and digital beamforming) [12].

![Beamforming (2D)](image)

**Figure 1.3: Beamforming (2D)**

With help of beamforming mm-waves can be efficiently used in a small cell, but given the upwards trend in human electronic usage, the base station in 5G must be able to handle a very high number of devices. So base station must be equipped with more antennas, using more individual antennas is not feasible. A better approach has to be employed. This leads to concept of MIMO [15], which is already available in LTE. It greatly counters the adverse effects of the channels. The capacity (number of UEs) requirement in 5G would be much higher than LTE, so employing massive MIMO would be a suitable idea.

Massive MIMO

One of the very interesting and very important advancement in telecommunications is Multiple Input Multiple Output (MIMO). We can exploit
1.2 Introduction to machine learning

Machine learning is an alternate approach to conventional engineering approaches to problem solving. It basically uses a training set to train the algorithm, which produces a trained machine to perform the task. Training set contains a large number of samples of similar behaviour. Combination of training set and algorithm are used to predict the output or perform the task. This has been illustrated in figure 1.4. Machine Learning (ML) has been a trend in the tech world now a days, it can be a very powerful tool depending on the application. During the implementation phase of this work, an issue was detected, which will be discussed in the following chapters. Conventional engineering approach was not sufficient to resolve this error. So, the preferred choice was to use ML approach. ML has already been used in PRACH [13]. This gives us the motivation to use machine learning in this work. There are two types of techniques in machine learning,

- Supervised Learning: Supervised learning uses the input (known) data and response (known) of the training data to train the model and
predict the response of the new input. The idea is to train the machine on the mapping between input and response [24]. So, when testing set is applied, it can use its learning to predict the output. Usually the there will be a label to distinguish between different classes.

- Unsupervised Learning: Unsupervised learning is used to find patterns or groupings which are hidden in data. Unlabelled inputs are the samples in training set. i.e, the points in the 2 dimensional plane will not provide any indication of the output [24].

Supervised learning is more suitable to this work as it seems to be a classification problem.

1.3 Structure

Structure of the this work can be explained in the following way. Concepts in New Radio (NR) will be explained in chapter 2 which covers various aspects of the work in context. Machine learning has been an important study in this work, which will be discussed in chapter 3. Then, implementation of the transmitter and receiver of physical random access channel (PRACH) in new radio will be discussed in chapter 4 followed by simulation results in chapter 5.

It is important to understand the frame structure in NR, which is very crucial for transmission of not only preambles but the data is well, this is discussed in section 2.1. The channel in context of this work is PRACH, which will be discussed in section 2.2 and section 2.3 provides the insights into various formats in PRACH. Machine learning and its types are discussed in section 3. Various considerations in the description for the implementation of the transmitter and receiver are discussed in section 4.1, where as implementation of machine learning is discussed in section 5.2. Results of the simulation of the initial implementation of the receiver (version 1) are furnished in section 5.1 and results of the various classifiers used in machine learning part of the receiver are described in section 5.2. The discussion finally ends with a conclusion.
CHAPTER 2

New Radio

This chapter gives the insight into various factors involved in physical layer in 5G, details of PRACH and formats that are developed for 5G are described.

2.1 Frame structure

The frame structure in New Radio (NR) looks similar to frame structure type 2 in LTE with some changes as the bandwidth in NR is significantly higher and a new concept called numerology is introduced in NR. As a consequence now the frame structure in NR is slightly different.

Numerology

NR now supports multiple OFDM numerologies as given in table 2.1, where $\mu$ is subcarrier spacing configuration. This is the fundamental difference between LTE and NR, LTE has a fixed sub carrier spacing for uplink. [6]
Chapter 2. New Radio

<table>
<thead>
<tr>
<th>$\mu$</th>
<th>$\Delta f = 2^{\mu}.15$[kHz]</th>
<th>Cyclic prefix</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>15</td>
<td>Normal</td>
</tr>
<tr>
<td>1</td>
<td>30</td>
<td>Normal</td>
</tr>
<tr>
<td>2</td>
<td>60</td>
<td>Normal, Extended</td>
</tr>
<tr>
<td>3</td>
<td>120</td>
<td>Normal</td>
</tr>
<tr>
<td>4</td>
<td>240</td>
<td>Normal</td>
</tr>
</tbody>
</table>

Table 2.1: Random access preamble parameters

Frames and subframes

All the downlink and uplink transmissions are organized into frames of 10ms duration. Each frame is divided into two half frames, which is further divided into 5 subframes. So, each frame consists of 10 sub frames which can be observed in figure 2.2. These sub frames are numbered from 0 to 10, each subframe is divided into slots. Number of slots per subframe depends on the subcarrier spacing configuration $\mu$, this can be observed in table 2.2 and 2.3. See [5] for more details.

Both uplink and downlink on a carrier has a set of frames. For transmission from the User Equipment (UE), the Uplink frame number $i$ would start $T - TA = (N_{TA} + N_{TA,offset})T_c$ before the start of the corresponding downlink frame at the UE where $N_{TA,offset}$ depends on the frequency band [5].

![Uplink-Downlink timing relation](image)

Figure 2.1: Uplink-Downlink timing relation
2.1. Frame structure

<table>
<thead>
<tr>
<th>$\mu$</th>
<th>$N_{\text{slot, symb}}$</th>
<th>$N_{\text{frame, }\mu}$</th>
<th>$N_{\text{subframe, }\mu}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>14</td>
<td>10</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>14</td>
<td>20</td>
<td>2</td>
</tr>
<tr>
<td>2</td>
<td>14</td>
<td>40</td>
<td>4</td>
</tr>
<tr>
<td>3</td>
<td>14</td>
<td>80</td>
<td>8</td>
</tr>
<tr>
<td>4</td>
<td>14</td>
<td>160</td>
<td>16</td>
</tr>
</tbody>
</table>

Table 2.2: Number of OFDM symbols per slot, slot per frame and slots per normal cyclic prefix

<table>
<thead>
<tr>
<th>$\mu$</th>
<th>$N_{\text{slot, symb}}$</th>
<th>$N_{\text{frame, }\mu}$</th>
<th>$N_{\text{subframe, }\mu}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>12</td>
<td>40</td>
<td>4</td>
</tr>
</tbody>
</table>

Table 2.3: Number of OFDM symbols per slot, slot per frame and slots per extended cyclic prefix

Figure 2.2: Frame structure

Physical resources

Resource grid, which contains resource elements is depicted in figure 2.3. A resource element is the basic time frequency resource in slot. Each slot has 14 OFDM symbols, each symbol has up to 4096 subcarriers. This combination of OFDM symbols and subcarriers are organized into resource blocks as shown in figure 2.3. See [5] for more details.
Bandwidth part is an important concept introduced in NR. As NR has different subcarrier spacing, so each subcarrier spacing could lead to a different bandwidth with the same number of subcarriers. A bandwidth part contains the subcarriers with same frequency spacing as shown in figure 2.4. A UE can be configured with up to four bandwidth parts in the downlink with a single downlink bandwidth part being active at a given time.
2.2 PRACH

Physical Random Access Channel, similar to LTE is the channel responsible for Random Access Procedure. This channel in physical layer co-exists along with physical uplink control channel and physical uplink shared channel. As this is in the uplink, now the transmitting part is user equipment. UE selects a preamble out of available preambles on that RACH occasion and then it will be transmitted to the base station. Now new radio supports OFDMA along with SC-OFDMA (only available option in LTE).

**Preamble**

In NR the Preamble is generated from the Zadoff Chu (ZC) sequences as already done in LTE, see [5]. ZC sequences are chosen for their partic-
ular properties as Cyclic auto correlation. This is a very key property in PRACH as it helps generate more preambles with single root \[5\], which is definitely an advantage. The structure of the preamble is shown in the following figure.

\[
\begin{array}{|c|c|c|}
\hline
\text{CP} & \text{Sequence} & \text{GP} \\
\hline
\end{array}
\]

**Figure 2.5: Preamble structure**

So we have root sequence, which is the first preamble and then we shift the sequence cyclically by few samples \[5\](defined by Zero Correlation Zone) to get another sequence. We repeat this until we reach the end of the sequence. Once we reach the end, we choose a new root sequence and repeat the process until we have 64 sequences. There were many proposals as to how the preamble should be designed in order to compensate the delay spread and round trip delay. Initially there were 5 options considered \[10\]. Later, they (Members of 3GPP) chose two options to proceed further, see \[9\] for details. As the structure of the sequence has been decided, now sequence length and subcarrier spacing have to be decided. Length of the sequence has been chosen the same as of LTE for the similar reasons. But the subcarrier spacing is what differentiates the PRACH in NR with PRACH in LTE. As in LTE case below 6GHz, a subcarrier spacing of 15kHz is robust to frequency errors in low speed scenarios. But in New radio a subcarrier spacing of 30kHz has been opted for high speed scenarios. One of the key factor in NR is the frequency spectrum, now we want to use higher frequencies, higher than 6 GHz. In these higher frequencies subcarrier spacing of 120kHz, 240kHz are opted by 3GPP members as they are robust. Another subcarrier frequency opted is 480kHz but it is currently not in use. So now we have sequence length of either 839 or 139 and the subcarrier spacing 15kHz, 30kHz, 60kHz, 120kHz, 240kHz, 480kHz. We can formulate the subcarrier spacing in the following way.

\[\Delta f = 2^\mu \times 15 kHz \quad \mu = 0, 1, 2, 3, 4, 5\] (2.1)
2.2. PRACH

The combination of sequence length and subcarrier spacing is as follows, L = 839 does not support frequencies above 6GHz and L= 139 supports 60kHz,120kHz and 240kHz above 6GHz and 15kHz, 30kHz are supported below 6GHz.

Zadoff - Chu sequences

Zadoff Chu (zc) sequences are the choice of sequences for the preamble signatures. It is the same case even in LTE. As earlier discussed there sequences have cyclic auto correlation property which is very crucial here.

\[ a_q(n) = e^{j2\pi \frac{2}{N_{ZC}} + l \cdot n}, \quad l \in N \]  \hspace{1cm} (2.2)

\[ q \in \{1, 2, \ldots, N_{zc} - 1\}, \quad n = 0, 1, 2, \ldots, N_{ZC} - 1 \]  \hspace{1cm} (2.3)

\( q \) is the root index and \( N_{ZC} = 839 \) or 139

The sequence would be like \{ \( a_q(0) \), \( a_q(1) \), \ldots \ldots, \( a_q(N_{ZC}) \) \}, we would have 839 chirps for \( L = 839 \) sequence or 139 chirps for \( L = 139 \) sequence.

These sequences has following properties [25]

1. Sequence and its \( N_{ZC} \) point has constant amplitude

2. Ideal cyclic auto correlation

3. The value of the cyclic cross correlation between any two Z-C sequences is \( \frac{1}{\sqrt{N_{ZC}}} \) if \( |q_1 - q_2| \) is relatively prime with respect to \( N_{ZC} \)

Base band signal

The base band signal is different from LTE base band signal. It is specified by 3GPP [5]

\[ S^{(p,R)}_l (t) = \sum_{k=0}^{L_{RA}-1} a_k^{(p,R)} \Delta e^{j2\pi (k+Kk_1+\bar{k})f_{RA}(t-N_{G_{C,l}T_c-t_{start}})} \]  \hspace{1cm} (2.4)
Chapter 2. New Radio

\[ K = \Delta f / \Delta f_{RA} \]

\[ k_1 = k_0^\mu + (N_{BW_{start,i}}^{start,\mu} - N_{grid}^{start,\mu})N_{sc}^{RB} + n_{RA}N_{RB}^{RA}N_{sc}^{RB} - N_{grid}^{size,\mu}N_{sc}^{RB}/2 \]

\[ k_0^\mu = (N_{grid}^{start,\mu} + N_{grid}^{size,\mu}/2)N_{sc}^{RB} - (N_{grid}^{start,\mu_0} + N_{grid}^{size,\mu_0}/2)N_{sc}^{RB} 2^{\mu_0-\mu} \]

where \[ t_{RA}^{start} \leq t < t_{RA}^{start} + (N_u + N_{CP,l}^{RA})T_c \]

### 2.3 Formats

As we have different user requirements we need different lengths for cyclic prefix and sequence length (in time units defined earlier). So different combinations of length of the sequence, length of the cyclic prefix and subcarrier spacing are organized into different formats. The format of the sequence that we choose is very important as it changes everything. As usual formats of the longer sequence (L = 839) are designed similar to LTE. The real change appears in the formats of the shorter sequence (L = 139), as it now has many formats to support the flexibility that is expected of NR.

The first difference between long sequence formats and short sequence formats is coverage area and latency. The c-plane latency should be less for formats with shorter length, and longer sequences should obviously provide much better coverage at low frequencies. More over short sequence formats does not need restricted set of cyclic shifts. There are 4 formats for long sequence length (L = 839), Format 0, format 1, format 2, and format 3. Basically there are 3 types of short sequence (L = 139).

1. Type A
2. Type B
3. Type C

- Type A formats: These formats don’t have any guard period at the end of the sequence (see figure 1). So, it is limited in terms of the coverage area. Especially when it is followed by data symbols, as we don’t have any guard period. Then how about the interference between prach and pusch symbols?, well the cyclic prefix of the
2.3. Formats

data in pusch will act as a guard period. So, format A can accept
the delay spread as big as that of cp of the data sequence. This is
how it is limited in terms of coverage as the cp of data sequence is
very small.

NOTE: The best way to use these formats is when scheduler sched-
ules PRACH occasion followed by another PRACH occasion, then
we can use these formats as the cp of the next sequence will act
as the guard period for the previous one. Incase if you do want
to multiplex these with the data sequences then it is better to leave
an entire OFDM symbol as the guard period (which is a waste of
resource), this can be seen in figure 2 and 3.

- Type B formats: These formats will cover up the issue of Type A
  formats as it has a guard period. So, we don’t have to waste an
  entire OFDM symbol just for the guard period specially given that
  we are using these formats in much smaller cells. So, it can be
  better multiplexed with data.

  We can also multiplex the Type A format followed by Type B for-
  mat followed by data symbols, this way we don’t have to be worried
  about the guard period before the data symbols. See [23] for details.

- Type C formats: Another limitation of Type A formats apart from
  multiplexing is the coverage, even with Type B formats we cannot
  enhance the coverage as its cyclic prefixes are in the same range to
  that of Type A. To enhance the coverage, we need more cyclic pre-
  fix, that is when these formats come into context. If you observe the
  cp of these formats (figure 1) is considerably high, providing better
  coverage. Now the question is why do we need Type A formats
  when we have Type C formats which can provide better coverage.
  The answer would be simple, if you observe the Type A or Type B
  sequences, they exactly match with the boundaries of data/control
  symbols (refer to Figure 4). But whereas type C doesn’t have that
  facility. See [23] for details. After all, it is always good to have
  options, so that we can use the resources much better.

The finalized formats as per 3GPP are shown in the following tables
2.5 and 2.4. Each format has different values for the parameters which
Chapter 2. New Radio

Table 2.4: Preamble formats for \( L_{RA} = 139 \)

<table>
<thead>
<tr>
<th>format</th>
<th>( L_{RA} )</th>
<th>( \Delta f^{RA} )</th>
<th>( N_u )</th>
<th>( N_{CP}^{RA} )</th>
<th>Support for restricted sets</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>139</td>
<td>15.2( \mu )kHz</td>
<td>2.2048K.2( \mu )</td>
<td>288K.2( \mu )</td>
<td>-</td>
</tr>
<tr>
<td>A2</td>
<td>139</td>
<td>15.2( \mu )kHz</td>
<td>4.2048K.2( \mu )</td>
<td>576K.2( \mu )</td>
<td>-</td>
</tr>
<tr>
<td>A3</td>
<td>139</td>
<td>15.2( \mu )kHz</td>
<td>6.2048K.2( \mu )</td>
<td>864K.2( \mu )</td>
<td>-</td>
</tr>
<tr>
<td>B1</td>
<td>139</td>
<td>15.2( \mu )kHz</td>
<td>2.2048K.2( \mu )</td>
<td>216K.2( \mu )</td>
<td>-</td>
</tr>
<tr>
<td>B2</td>
<td>139</td>
<td>15.2( \mu )kHz</td>
<td>4.2048K.2( \mu )</td>
<td>360K.2( \mu )</td>
<td>-</td>
</tr>
<tr>
<td>B3</td>
<td>139</td>
<td>15.2( \mu )kHz</td>
<td>6.2048K.2( \mu )</td>
<td>504K.2( \mu )</td>
<td>-</td>
</tr>
<tr>
<td>B4</td>
<td>139</td>
<td>15.2( \mu )kHz</td>
<td>12.2048K.2( \mu )</td>
<td>936K.2( \mu )</td>
<td>-</td>
</tr>
<tr>
<td>C0</td>
<td>139</td>
<td>15.2( \mu )kHz</td>
<td>2048K.2( \mu )</td>
<td>1240K.2( \mu )</td>
<td>-</td>
</tr>
<tr>
<td>C2</td>
<td>139</td>
<td>15.2( \mu )kHz</td>
<td>4.2048K.2( \mu )</td>
<td>2048K.2( \mu )</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 2.5: Preamble formats for \( L_{RA} = 839 \)

<table>
<thead>
<tr>
<th>format</th>
<th>( L_{RA} )</th>
<th>( \Delta f^{RA} )</th>
<th>( N_u )</th>
<th>( N_{CP}^{RA} )</th>
<th>Support for restricted sets</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>839</td>
<td>1.25 kHz</td>
<td>24576K</td>
<td>3168K</td>
<td>Type A, Type B</td>
</tr>
<tr>
<td>1</td>
<td>839</td>
<td>1.25 kHz</td>
<td>2.24576K</td>
<td>2.21024K</td>
<td>Type A, Type B</td>
</tr>
<tr>
<td>2</td>
<td>839</td>
<td>1.25 kHz</td>
<td>4.24576K</td>
<td>4688K</td>
<td>Type A, Type B</td>
</tr>
<tr>
<td>3</td>
<td>839</td>
<td>5 kHz</td>
<td>4.6166K</td>
<td>3168K</td>
<td>Type A, Type B</td>
</tr>
</tbody>
</table>

translates to different lengths for sequence and cyclic prefix in time. An example of format 0 has been depicted in figure 2.6

Figure 2.6: Format structure [\[1\]]
CHAPTER 3

Machine Learning

This chapter deals with basics of machine learning, i.e., types of machine learning and their description. The description of algorithms that are chosen for this work can be found in this chapter.

3.1 Machine learning

Machine Learning basically teaches machines to learn things in the same way that we learn. Humans learn from their experience (remembering the past), in machine learning it is no different, machines remember the past data and predict the future based on the data it has. So data is very crucial here. There is no predetermined rule a formula to follow. It is simply trial and error process. Once the data is analyzed, the algorithm must be chosen. Sometimes, it is easy to find an algorithm and sometimes it is rather difficult. It depends on how well the data can be distinguishable. There are two types in Machine learning, classification and regression. The topic of regression is not in interested for this work as the issue is more suitable to classification.
3.1.1 Supervised Learning

Supervised learning uses the input (known) data and response (known) of the training data to train the model and predict the response of the new input. The idea is to train the machine on the mapping between input and response [24]. So, when testing set is applied, it can use its learning to predict the output. Usually there will be a label to distinguish between different classes, see figure 3.3 where it can be observed that the data is labelled as preamble and false peak. Supervised learning is applied in filtering the spam emails, which is a well known example. There are two techniques in Supervised learning.

- Classification
- Regression

Classification

This technique predicts discrete responses for given input. It distinguishes the input data in to different classes and then predicts response of new input depending on which class that it belongs to. There are two types of classifications

- Binary classification: As the name suggests, there will be two classes to choose from. It is the simplest classification.
3.1. Machine learning

- Multiclass classification: This is more complex classification, as there are multiple classes that new data point can belong to. Often multiclass classification is subdivided into binary classifications for better execution.

![Figure 3.2: Multiclass classification](image)

In binary classification there are only two classes (or responses) to choose from, whereas in multiclass classification there are multiple classes (or responses) to choose from and it is more complex than binary classification. There are several models available for classification:

- Logistic regression
- $k$ nearest neighbors ($k$-NN)
- Discriminant analysis (DA)
- Naïve Bayes (NB)
- Decision tree
- Support vector machines
- Neural networks

Following classifiers are chosen for implementation for the reasons that will be explained in the following chapters.
Chapter 3. Machine Learning

$k$ Nearest Neighbors

It is a simple model to start with and categorizes the data based on the class of its neighbors. see [11] for details. Distance metrics such as Euclidean, blocks, Chebyshev, cosine are used to find the nearest neighbors. Advantage of \( k \)-NN is that it is very simple to understand, but it is slow compared to other classifiers, reason being it has to calculate the distance between the data in context and all the data points in the training set (which some times could be large). But this is a good classifier to begin with.

![Figure 3.3: \( k \)-NN classification](image)

Generally the distance among training set and testing set is calculated using Euclidean distance formula

\[
d_{xy} = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}
\]  

(3.1)

Decision Tree Classification

One of the disadvantage of the \( K \)-NN is that it has to calculate the distance between the new data point and the entire training data points, which takes time. Decision trees is superior to \( K \)-NN in terms of computational speed with more or less similar accuracy. The advantage of
3.1. Machine learning

DTC is its ability to breakdown complex decision making process into simple decisions [22]. As it can be seen in figure 3.5, a set of decisions are taken at each internal node (point where decision is taken) to decide the class of the response. The most important thing here is the design of tree.

![Illustration of DTC](image)

Figure 3.4: *Illustration of DTC*

![Decision process in DTC](image)

Figure 3.5: *Decision process in DTC*

The tree design (from Bayes point of view) may be studied as the following optimization problem [22]
Chapter 3. Machine Learning

\[ \min( P_e(T, F, d)) \]  \hspace{1cm} (3.2)

Where \( P_e \) is the overall error probability, \( T \) is a specific tree structure, \( F \) and \( d \) are feature subsets and decision rules, which are used at internal nodes. See [22] for more details.

Naïve Bayes (NB)

Perhaps one of the most efficient classifiers in machine learning with lot of applications. This is much faster and more accurate and less prone to outliers. It works on the basis of Bayes principle [14].

\[ P(B)P(A|B) = P(B|A)P(A) \]  \hspace{1cm} (3.3)

![Figure 3.6: NB classification](image)

This classifier will assign a probability distribution to each response class in the training set, which will give us \( P(\text{position}|\text{response class}) \), by invoking Bayes theorem \( p(\text{response class}|\text{position}) \). Since there are two response classes, we get two probabilities i.e, probability of false peak response class given its position and probability of original peak response class given its position. Now the decision can be made for the class of testing data point by observing the probabilities. NB chooses the most probable class as the class of the testing data point. Advantage of
this classifier is it is not prone to noise (outlier) as it will have a very low probability that it belongs to the original set, this can be seen in figure 3.6

### 3.1.2 Unsupervised Learning

Unsupervised learning is used to find patterns or groupings which are hidden in data. Unlabelled inputs are the samples in training set. i.e, the points in the 2 dimensional plane will not provide any indication of the output. As it can be observed in figure 3.7, there are no labels for data points in the training set. Instead the data are clustered to find the pattern in the data which separates the 3 groups shown in figure 3.7. Once the closer points are clustered together, they will be assigned with a label called cluster label [24]. Unsupervised learning techniques are used to cluster the documents of similar topics.

![Figure 3.7: clustering in unsupervised learning](image)

Clustering is the most commonly used method. There are multiple models available for clustering.

- K Means clustering
- Hierarchical
Chapter 3. Machine Learning

- Gaussian mixture
- Hidden Markov model
- Neural Networks

Figure 3.8: Machine learning algorithms [2]
In this chapter the implementation of the transmitter and receiver, consider-ations and the issues that were identified with the implementation of the receiver based on LTE receiver, which is the starting point for this work are discussed. Along with this, implementation of the receiver based on machine learning and classification algorithms chosen for this purpose are discussed.

4.1 Considerations and Implementation

The simulator of transmitter and receiver has been implemented in mat-lab. Following are the important parameters chosen for the implementa-

- I chose PRACH configuration index = 27 (see table 6.3.3.2-2 in [8]). This is a very important parameter as it decides the sub frame number in which preamble can be transmitted.

- I chose format 0, so that we can compare the performance of this implementation to the performance of LTE [4]. See table 2.5 for details of format 0.
Chapter 4. PRACH detection approach

- I considered Bandwidth = 20 MHz as it is the same bandwidth considered for performance evaluation in LTE. The performance target that we are trying to achieve is the performance threshold defined for LTE.

- I considered Zero configuration zone 1, which gives $N_{CS} = 13$ (see table 6.3.3.1-5 in [8]), I chose this as this is the smallest sample size that can be considered. Small sample size means more windows to be detected which is the worst case for detecting errors.

- I considered subcarrier spacing of PRACH and PUSCH to be 15 kHz (see table 6.3.3.2-1 in [8]).

- I considered Frequency division duplex (fdd) for duplexing and $\mu = 0$ (Numerology).

Considerations that were made so far are suitable to the mobile broadband communication in NR. The process of implementation has been explain in the following sections.

4.1.1 Transmitter

PRACH now supports OFDMA along with SC-OFDMA. In this implementation, we decided to use OFDMA, hence the transmitter has been slightly changed for New Radio compared to LTE. The block diagram of the transmitter is depicted in figure 4.1.

The idea is to use the transmitter and receiver that was developed for LTE and adapt it to comply with 5G standard defined by 3gpp specification. Here the adaptation means modifying the simulator such that it accepts the new changes introduced in NR, without changing the overall simulator. The initial assumption is that it may work well given the changes introduced by 3gpp for NR in PRACH are comparatively low. The block diagram of the transmitter is depicted in figure 4.1. It turns out that the idea was not bad as the transmitter part worked out with out any issues. As NR supports both SC-OFDMA and OFDMA [8], OFDMA has been adapted for the implementation of the transmitter as it is the scheme opted by 3GPP [8] for base band signal generation.
4.1. Considerations and Implementation

Figure 4.1: Transmitter

The transmitter block diagram has been depicted in figure 4.1. First root sequence has to be generated with all the considerations mentioned in the previous section. One of the advantages with zadoff - chu (ZC) sequences is that they can be generated in both time domain and frequency domain. Here the frequency domain sequence generation has been opted as it would be compatible with the OFDMA. Now the preamble has to be mapped to the subcarriers. The next step would be to convert this frequency domain signal to time domain by applying IFFT. The preamble generation depends on the format that is chosen, as it can be observed in the table each format has different sequence and cyclic prefix (cp) lengths. After inserting the cp, the time domain signal will be transmitted to the RF section. RF section, which contains the antenna will transmit the signal to the gNodeB. RF section is not implemented in this simulator. The channel in use is AWGN, this was chosen as starting point with possible extension to other complex channels.

4.1.2 Receiver

Most important part of the simulator is the receiver as it has to be adapted well to get the required performance. At the beginning of this thesis the performance threshold was not given [3], so LTE performance [4] was considered as the working threshold. It is only in January 2019, 3GPP defined the performance requirement for NR [7], by which the implementation was almost completed. The receiver block diagram is shown in the figure 4.2.

Figure 4.2: Receiver (Two stage detection)
Chapter 4. PRACH detection approach

Implementation process of the receiver can be seen illustrated as follows.

- The first step after receiving the signal would be to remove cp and guard period as shown in the figure 4.2.
- The signal has to be transformed to frequency domain and then the process of de mapping has been implemented.
- Decimation helps the receiver to reduce the number samples in the sequence to be processed, otherwise it would be challenging to apply FFT to a sequence with large number of samples.
- Power delay profile (pdp) will be generated by performing the auto correlation of the received signal with the selected root sequence, as the ZC sequence has cyclic auto correlation properties.
- As the pdp is computed, now the received signal has to be detected. The basic idea detection is to set a threshold, which can be used to detect peaks which are higher than this threshold value. It is implemented in two stages. First stage contains an up sampling filter and peak search. After filtering, threshold (which is defined prior to this) will be used to detect the peak. Second stage contains a low pass filter and peak search. This stage reduces the impact of the delay spread of the channel. For more details on detection part see [18].
- If the receiver detects the preamble, the position of the peak in the pdp will give us the timing advance which is very important for initial synchronization of the user equipment to gNodeB.

For testing the simulator, one preamble was sent in every time interval (TTI) because of the chosen configuration defined by 3GPP index [8]. Every pdp that was computed should contain one large peak at moderate SNR scenarios (when the impact of the noise is moderate), instead sometimes the pdp contains two strong peaks (see figure 4.3), this is when the detector will detect two preambles instead of one. The reason for this strong second peak could not be identified, due to the random nature of this peak. The threshold of the detector is not sufficient to avoid the
second peak. This will lead to more number of received preambles than sent, which is an error and this impacts the performance of the receiver.

![Figure 4.3: Power delay profile (Single correlation)](image)

Given the nature of the issue, machine learning seems to be the correct choice as it can learn the behaviour of the false peak and predict the possible scenarios where it might appear. At the first glance it looks like the classification issue in ML. Classification algorithms under supervised learning are adapted in the receiver with the goal of classifying the false peak with the original peak.

### 4.2 Implementation of machine learning

The idea is to replace the filtering techniques in detection stage \[18\] by machine learning techniques to determine the correct peak, so that the performance can be improved. The changes in the detection part are shown in the following block diagram.

![Figure 4.4: Detection part in the receiver (with machine learning)](image)
Before adapting machine learning in the detection stage, it is better to choose what are the suitable classifiers. Matlab provides a useful machine learning tool to compute the prediction accuracy of different classifiers. But it requires a training sequence.

![Training Data](image)

**Figure 4.5: Training Data**

![Training data magnified at low SNR region](image)

**Figure 4.6: Training data magnified at low SNR region**

The idea is to collect the data using the initial implementation of the receiver. Variables chosen for the training sequence are mean, variance and peak value of the pdp, as they are the first parameters that could vary from pdp to pdp, which gives us a range of data to classify the
4.2. Implementation of machine learning

peaks. After collecting the data, which can be seen in figure 4.5, different classifiers were tested using the machine learning tool in MATLAB. Three algorithms which had the better accuracy were chosen to be adapted into the receiver. Those are $k$ - Nearest Neighbors ($k$ - NN), Decision Tree classification (DTC) and Naïve Bayes (NB) classification.

$k$ - NN is the first classifier employed in the detector to predict the output. It worked well at low to medium SNR range, but at high SNR range the curve started to rise (see figure 5.3). Reason found for this issue is that at high SNR values the mean and variance of the false peak pdp are in similar proximity of original peak. This leads the classifier to bias the decision towards original peak.

Then DTC, which had the similar prediction accuracy was employed in place of $k$ - NN to see if the problem persisted. Even it had the same result for the same reason. The result can be observed in the following chapter (see figure 5.5). The distance metric used here is Euclidean and value $k = 4$.

As a final choice, NB was employed in the detector, but unfortunately, this classifier had even worse results in an opposite behaviour to the other classifiers. This will lead to a hybrid method, which will be discussed further. The behaviour of the curve (see figure 5.7) is definitely not good at low SNR but it has a very good trend at high SNR. Reason for this quite an opposite behaviour to other classifier discussed earlier is the probability distribution. This reason is explained clearly in the following chapter.

After realizing that there is decision bias in $k$ - NN and DTC, an other predictor (variable) is added to the data, i.e, the peak value, in an attempt to separate the false peak data from original peak data. This new data was applied to $k$ - NN classifier, the results were better (see figure 5.4) compared to previous figure 5.3. But the upward trend still persisted not as worse as it was in the previous case, but it sill is an issue.

Having realized that the behaviour of NB curve is opposite to that of other classifiers, the idea is to mix either $k$ - NN or DTC with NB to form a hybrid classifier which will provide the desired results. A switching point has been selected at -10 dB, because at this SNR value both classifiers (DTC and NB) has the same missed detection probability which is zero. This definitely improved the performance the modified receiver
Chapter 4. PRACH detection approach

to match the target. Results discussed in detail in the following chapter. The probability distribution used in NB implementation is normal distribution. According to central limit theorem [26] distribution of a sample set which contains the mean values of other sample set (it may follow any probability distribution) is a normal distribution. Here the variable in context is mean of a set of independent samples in a pdp. So, it is believed that this idea of using normal distribution may work. After trying different distributions, it was realized that using normal distribution is a good idea.
Simulation Results

Simulation results of various techniques used in this work are discussed in this chapter. Both, version 1 (adapted version of LTE simulator) and modified (based on machine learning) simulation results are presented in this chapter.

5.1 Results of the receiver (first version)

Implementation which is based on the receiver designed for LTE [18] which is the starting point for this work. Along with this, strengths and weaknesses of machine learning techniques that were employed in the implementation of the modified receiver and the idea of combining different classifiers to improve the results are discussed.

The performance of the first implementation of the receiver (adapted version of LTE receiver for NR) is shown in figure 5.1. As it can be seen the performance is not matching the target (specified by 3gpp) [4]. The observed degradation in the performance is due to the detection of false peak (which was discussed in the previous chapter). In order to improve the results, machine learning algorithms had to be integrated into the receiver. Prediction accuracy of several classifiers was tested by using
Chapter 5. Simulation Results

the machine learning tool in matlab with training data. \(k\)-NN, DTC, NB were chosen to help the receiver to detect only the correct peak as these had the better accuracy in terms of prediction.

![Figure 5.1: Performance of the receiver (version 1)](image)

\[\text{Missed Detection probability} = 10^{-2}\]

\[\text{SNR [dB]} = -20, -18, -16, -14, -12, -10, -8, -6\]

Figure 5.1: Performance of the receiver (version 1)

5.2 Results of the modified receiver

In the figure 5.2 we can observe the pattern of the training data which was collected using the initial implementation of the receiver (version 1). This plays a very crucial role in the performance of the modified receiver, impact of the pattern of training data will be explained in the following text. Performance of the modified receiver with different classifiers has been explained in the following sections.
5.2. Results of the modified receiver

Performance with $k$-NN classifier

As it can be observed in figure 5.3, $k$-Nearest Neighbors ($k$-NN) clearly meets the 3gpp requirement, which is good, but the performance is not consistent through out.

Figure 5.2: Collected Data (2 dimensions)

Figure 5.3: $k$-NN performance (with two predictors)
Chapter 5. Simulation Results

Figure 5.4: $k$-NN performance (with 3 predictors)

As it was discussed in the previous chapter the values of mean and variance of the pdp of false peak is similar to the original peak, which is biasing the decision in detecting more preambles. This will cause the detector to detect more preambles, which in turn will deteriorate the performance of the receiver. This deterioration can be observed in the figure 5.3.

An extra predictor has been added to the existing two predictors in an attempt to separate the data at high SNR, but it turned out that even with an additional predictor the upward trend observed in 5.3. However the results are much better to the previous case, this can be observed in figure 5.4.

Decision Tree classifier

Decision Tree Classifier (DTC) has the similar performance to that of $k$-NN. Even DTC has the same upwards trend at high SNR for the same reason mentioned in the previous section (see performance of $k$-NN). The performance of DTC is shown in the following figure.
5.2. Results of the modified receiver

Figure 5.5: Performance of DTC

Naïve Bayes classifier

Naïve Bayes (NB) is one of the best classification algorithms and highly immune to noise (outliers). Unfortunately it has the worst performance among all the classification algorithms. At low SNR NB classifier consider the data that belongs to response class of the preamble as outliers, reason for this the assigned probability distribution, each response class in the training data will be assigned with a probability distribution. So any data from other response class will be an outlier. Unfortunately at low SNR, data points that belong to original peak fall in the region of false peak response class, which can be observed in 5.2. This will lead the classifier to bias the decision towards false peak irrespective of the actual class. This impacts the performance of the receiver in a big way, this is the reason why we see worse performance at low SNR as shown in figure 5.6. The exact opposite will happen at high SNR, so we have very good performance as shown in figure 5.6. Though it has worse performance at low SNR, it certainly has a significantly better performance at high SNR compared to other two classifiers.
Chapter 5. Simulation Results

Figure 5.6: Performance comparison of Naïve Bayes classifier

Figure 5.7: Performance comparison of 3 classifications

Hybrid technique

Clearly no classifier can help the receiver to achieve the consistent performance from low to high SNR. As we have seen so far, NB has the per-
5.2. Results of the modified receiver

Performance which is quite opposite to the other two classifiers. So using either $k$-NN or DTC with NB, we can produce the results which not only satisfies the 3gpp requirement but also has consistency throughout. A hybrid technique has been employed in the detection part of the new receiver to get the satisfying performance. For low SNR values DTC will be the active classifier and for high SNR values NB will be active. The switching point has been decided at SNR = -10 dB, as we can observe in figure 5.7, it gives us the best compromise. The performance of the receiver integrated with hybrid machine learning technique can be seen in the figure 5.8.

![Missed Detection probability - 2 RX AWGN](image)

**Figure 5.8: Performance of the new receiver**

The performance shown in figure 5.8 is better compared to the performance of the previous implementation of the receiver (version 1) shown in 5.1, hence use of machine learning has been justified. We have recently published these results and the publication has been accepted [18].
The objectives of this work is to implement a simulator for Physical Random Access Channel (PRACH) in 5G. That means implementing a transmitter and receiver which complies with 3GPP specifications. Our initial idea is to adapt a simulator that was already developed for LTE and test if it meets the performance requirement defined by 3GPP (But 3GPP did not define any performance threshold until January 2019, so we chose LTE performance threshold as the target). We believed that if we can deliver that performance with the existing detection algorithm, we could improve the results with some modification. The channel that we chose for the implementation is AWGN. After implementing the complete scheme, we detected an issue which was really complicated. The detector some times detected two peaks instead of one peak. This is so peculiar, we had to think differently to conventional approaches. This what laid a foundation to explore solutions based on machine learning. We were encouraged when we discovered that machine learning has already been used in PRACH [8]. We preferred not to follow that in an attempt to develop a technique which doesn’t has any influence.

Unlike conventional methods, machine learning works in different way. There is no set algorithm for a specific problem. It has to be trail and error process. Our idea is to use one of the machine learning algorithms to separate original peak from false peak. We have tried several classification algorithms to observe the variation in the performance. Af-
Conclusion

After several approaches, finally we used a hybrid method which provided the required performance. Use of machine learning has been justified by achieving the target, as it was not the preempted solution. We believe this work will encourage others to explore machine techniques to improve the performance of the existing systems.
Bibliography


Bibliography


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