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A machine learning-based design of PRACH receiver in 5G

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Abstract

The physical random access channel (PRACH) in the uplink of cellular systems is used for the initial access requests from users. In fifth generation (5G) systems three different types of services are available, which are massive machine-type communication, enhanced mobile broadband communication, and ultra-reliable low-latency communication. Considering the tight requirements in terms of latency, a robust design of PRACH receiver is one of the priorities. In this paper we first explore the simple extension of a technique proposed for fourth generation (4G) systems to 5G. Then we propose the application of machine learning techniques to make the PRACH receiver more robust to false peaks, which are responsible of performance degradation in the extension of the 4G technique to 5G. Monte Carlo simulations are used to evaluate and compare the performance of the proposed algorithms.

Keywords: Zadoff-Chu Sequence, PRACH, 4G, 5G, New Radio.

1. Introduction

In fifth generation (5G) technology three types of heterogeneous services are offered: enhanced mobile broadband (eMBB) communication, massive machine-type communication (mMTC), and ultra-reliable low-latency communication (URLLC) [1]. Due to the different requirements of these three services, a certain flexibility is required at different levels in the management of the time-frequency resources [2]. The efficient use of such resources is mainly impacted by the number of devices that require the initial access, which varies according to the type of service. This poses a challenge in the design of the physical random access channel (PRACH), whose performance must scale well with the number of devices.

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A first natural solution to address such a design is to extend PRACH algorithms proposed for fourth generation (4G) standards, i.e., Long Term Evolution (LTE) and LTE (LTE-A), by adapting them to 5G standard [3]. Since the random access channel procedure defined for 5G is the same as that used in 4G, the modifications of PRACH methods proposed for LTE and LTE-A must only take into account the differences in the frame structure according to 3GPP specifications [3]-[5]. This induces some changes in the operations implemented in the baseband processing during the initial access to achieve uplink synchronization and to detect the presence of a user.

In the literature, several methods were proposed to detect PRACH in 4G systems [6]-[9]. All the techniques have been designed to guarantee a probability of correct detection higher than 99% at signal-to-noise ratio (SNR) values greater than -14.2 dB, according to 3GPP TS.36.104 [4][2]. As one of the contributions of this work, we first adapt to 5G a technique we designed to detect the preamble in LTE and LTE-A. While the proposed technique allows to achieve a superior performance compared to techniques available in the literature for 4G, we show that when applied to 5G it suffers of a performance degradation. The main issue is that the receiver is affected by false peaks, which are less relevant in the 4G receiver. Motivated by this issue, we have explored other solutions. Among these, we here propose an approach based on machine learning (ML) [10]. It is worth observing that ML has already been applied to LTE-RACH [10] to improve the performance in collision detection and to reduce missed detection probability, load and latency. As is shown in [10] the achieved improvement is significant and this motivated us to explore ML techniques to enhance the performance in radio access networks (RAN).

The use of ML techniques seems to be particularly promising in facing with the issue of false peaks. Machine learning approaches allows for the use of smart algorithms that are able to discriminate false peaks. Therefore, we remove the filtering stage used in the original PRACH receiver designed for 4G and introduce ML algorithms to eliminate the false peaks issue and detect the preamble. Two different ML techniques are considered, which are naïve Bayes and *k*-nearest neighbors (*k*-NN) [12, 13]. The first, *k*-nearest neighbor (*k*-NN), is very simple but it is characterized by a very slow convergence. The second, the naïve Bayes method, is computationally faster than *k*-NN. Both are supervised machine learning methods, which help in classifying data. They are used in a hybrid way: *k*-NN, at very low SNR values and naïve Bayes, at SNR values higher than -10 dB. The advantages in terms of performance are demonstrated by means of Monte Carlo simulations considering the transmission over an additive white Gaussian noise (AWGN) channel, which is here used to test the performance of the proposed method.

The paper is organized as follows. Section 2 presents an overview of the preamble structure and introduces the definition of the error events that can occur in the preamble detection. The classical detection algorithm is introduced in Sec. 3. Section 4 illustrates the issues arising in a real implementation. In section 5 the proposed algorithms based on ML are described and numerical results are finally reported in Sec. 6. The conclusions are drawn in Sec. 7.

2. Preamble sequence construction and measure of performance

2.1. Construction of reference CAZAC sequence

The preamble sequences used in LTE and LTE-A are Zadoff-Chu (ZC) sequences, which satisfy the property of constant amplitude zero autocorrelation (CAZAC) [5]. This property is defined by ideal cyclic autocorrelation, where the correlation with a version of itself that is circularly shifted of N_{CS} samples is a Dirac delta function with a peak in N_{CS} positions. Considering a shift of $2N_{CS}$ we obtain another delta function with peak in position $2N_{CS}$ and so on. The number of samples between the peaks is called zero correlation zone (ZCZ) of the sequence and it guarantees the orthogonality of the PRACH sequences. It is worth observing that sequences that are obtained from cyclic shifts of different ZC sequences are not orthogonal. Therefore, orthogonal sequences obtained by cyclically shifting a single root sequence should be favored over non-orthogonal sequences. In LTE there are 64 possible sequences [5].

The preamble sequence used in 4G is obtained from the cyclic shift of a ZC sequence of prime length $N_{ZC} = 839$. The prime ZC sequence is defined as [4]

$$X_u(n) = e^{-\frac{j(\pi\, un(n+1))}{N_{zc}}}, \tag{1}$$

where $0 \leq n \leq N_{zc} - 1$ and u is the root of the sequence. All the 64 possible preamble sequences are obtained by cyclic shifts of the root sequence

$$X_{u,v} = X_u\big((n + C_v) mod N_{ZC}\big),$$

[2] Performance requirements for 5G in terms probability of correct detection were provided by 3GPP in January 2019, so our design was done considering the requirements defined for LTE-A.

where $mod(N)$ is the algebraic modulo N operation and

$$C_V = \begin{cases} vN_{CS} \quad v = 0,1,\dots,\left\lfloor \frac{N_{ZC}}{N_{CS}} \right\rfloor - 1, & N_{CS} \neq 0, \\ 0, & N_{Cs} = 0, \end{cases}$$

with $\lfloor\cdot\rfloor$ denoting the greatest integer lower than the number contained in it.

2.2. Definition of the error events

According to 3GPP technical specifications [4], three different error events can be defined:

1. $P_d(E)$, which is the probability of *not detecting* the preamble;
2. $P_{ta}(E)$, which is the probability of detecting the correct preamble detection but with the *wrong timing advance (TA) estimation*;
3. $P_w(E)$, which is the probability of detecting a preamble *different* from the one sent.

The sum of the three probabilities of error defines the total *missed detection probability*

$$P_{md}(E) = P_w(E) + P_d(E) + P_{ta}(E), \tag{2}$$

which is the performance measure to be minimized. Existing works address the problem of minimizing only $P_d(E)$. This is achieved by setting a threshold in agreement with the wanted false alarm probability [6, 7]. In this paper we propose an algorithm that consists in a three steps procedure, with the goal of minimizing the sum of the three terms.

3. Classic detection

The block diagram of the PRACH receiver chain is shown in Figure 1. The basic idea of the detection algorithm, which is implemented in the last block, is exemplified in Figure 2. By exploiting the properties of the ZC sequences defined above, a window-based detection approach is considered. The window has a size of N_{cs} samples, which corresponds to the size of the ZCZ. The detection consists in finding the highest value that exceeds a pre-calculated threshold for every searching window. The position of the highest value in the search window represents the delay of the preamble [6].

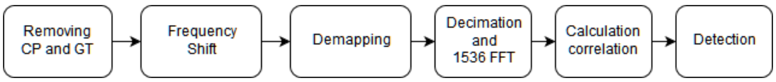

Figure 1. Block diagram of the PRACH receiver.

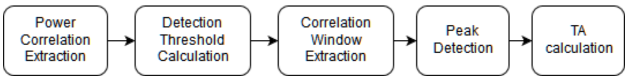

Figure 2. Block diagram of the detection algorithm.

The threshold calculation is detailed in the following. First of all, a theoretical threshold, called T_{TH}, is calculated assuming the case of ideal AWGN channel. As is well known, for a zero-mean complex AWGN channel the power envelope follows a central Chi-square distribution, where the degrees of freedom are determined by the number of Gaussian random variables that are summed together. By extending this concept to complex signals, the degrees of freedom are doubled, because these signals are the sum of two different random signals. Considering the received PRACH signal, the degrees of freedom include also the number of receiving antennas, because the total received signal is defined by the sum of the streams received by two receiving antennas. Then the average power of the correlation is calculated as

$$m_{tot} = \frac{1}{N_{sample}} \sum_{k=0}^{N_{sample}-1} pdp(k)$$

where $pdp(k)$ is the discrete-time power delay profile for the N_{sample} received samples. The threshold is set to

$$T_{total} = T_{TH} \cdot m_{tot}.$$

Then, the average power of the noise is estimated considering as noise all the samples smaller than T_{total} as

$$m_N = \frac{1}{N_{noise}} \sum_{k \in \mathcal{K}} pdp_{noise}(k), \tag{3}$$

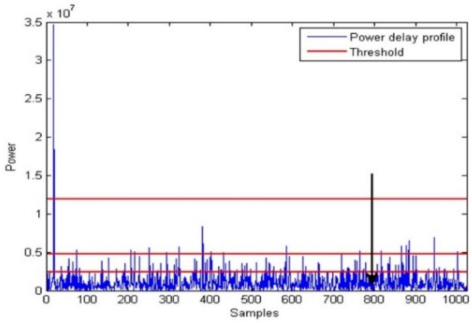

Figure 3. Undesired false peaks.

where $\mathcal{K}$ is the set of indexes of the pdp for which $pdp(k) < T_{total}$. The detection threshold T_{det} is calculated as

$$T_{det} = T_{TH} \cdot m_N. \tag{4}$$

The presence or the absence of a preamble is verified for every window by comparing each sample with the detection threshold level T_{det}. The maximum value in the window that is higher than T_{det} is the candidate preamble that is used to compute the preamble number and propagation delay. The identification of the preamble is defined by the index of the window where the threshold is exceeded, while the TA is defined by the position inside the window. In this paper the classical PRACH detection algorithm is referred to as one-step algorithm.

It is worth noting that the higher is Signal to Noise Ratio (SNR) and the lower is m_N and, therefore, the detection threshold. In this situation we observed several false peaks, as shown in Figure 3, where the threshold is computed at different SNRs. These undesired peaks, which are called side peaks, affect the missed detection probability by increasing $P_w(E)$ in (2). This is critical in the high SNR regime because the value of the threshold is too low. The solution adopted to face with this issue is to set a lower limit of the threshold and to redefine it when the threshold assumes a value less than this value as

$$if\ T_{det} < T_{detmin}$$
$$then\ T_{det} = T_{detmin},$$

where T_{detmin} is calculated sending several preambles at different SNRs. If T_{detmin} is too high there is a problem in the detection of correct preamble, while if it is too low the error detection increase. In high delay spread channel scenarios, i.e., extended terrestrial urban (ETU) proposed by International Telecommunication Union (ITU), this issue is critical because the side peaks issues are caused not only by the AWGN noise, but also from multipath, as observed after several simulations. This is due to the coherent sum of multipath, which is not negligible. The power accumulated on side peaks can exceed the threshold, based on the average noise power. Hence, a different detection algorithm is required.

The scenario is described in [14], where it is considered as maximum TA the one that corresponds to half of the cell radius. Our simulations have been done considering a more stringent requirement for a distance of 2/3 the cell radius, in order to have more conservative results. A uniform distribution of the users between 0 and 2/3 of the cell radius has been considered in place of than between 0 and half the radius, as suggested in [14].

4. Proposed three steps detection algorithm

All the issues mentioned in the previous section can be dealt with by analyzing two different aspects. The first is the missed detection and the second is the choice of a preamble in an incorrect window. The missed detection depends on the threshold calculation and on the setting of its value. As seen above the side peaks issue is critical in a high delay spread scenario, as those met in the ETU channel defined by ITU. Starting from this observation, the proposed algorithm is based on the idea of combining a predetermined number of adjacent samples in time in order to condense the effect of the channel in the actual position of the correlation. This allows us to reduce the power of the side peaks and, at the same time, to increase the accuracy in the estimation of the TA. The proposed detection algorithm can be split in three different steps as depicted in Figure 4, which are described in the following.

The first step is the one step detection described in Sec. 3. The searching window under analysis is processed and the first highest peak that exceeds the threshold is searched. The second step, which consists in a filtering operation

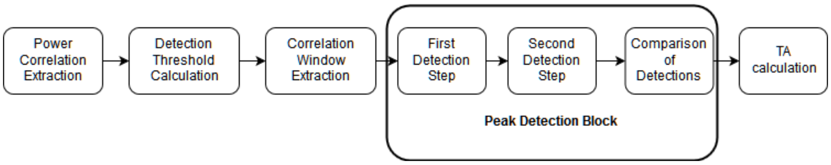

Figure 4. Three steps detection algorithm.

within the window under analysis, reduces the effect of the delay spread. Since the searching window has dimension N_{CS}, the length of the filter could not be too long otherwise the TA estimation is affected. The best dimension K of this filter is found after several simulations, which is a key parameter of the proposed algorithm. In the last step, the third, it is decided when a detection occurs and which detection is the most reliable between the two steps. The decision if a detection happened or not is different for the low or the high SNR scenario. For the low SNR scenario, a detection happens if at least in one of the two steps there is a crossing of the threshold. In the high SNR scenario, a detection happens if in both the steps there is a cross of the threshold. This is done to reduce the detection error due to side peaks. Then, when a detection happens, there are two different situations:

1. only one step has a crossing of the detection, which means its information is taken as correct;
2. both the steps have a detection, which means the peak with the highest power is considered as the most reliable one.

5. Machine learning basics

The basic principle behind ML is the prediction of the possible outcome by observing previous data, which is very similar to the way human behave based on previous experience. When enough data are available a machine can be trained to learn from the past data to predict the next outcome [15]. Two approaches can be used in ML:

1. Supervised learning, where the model is trained with input data and responses to the inputs. After the initial training, when a new input data is available, it is possible to predict the response based on what was learned prior to that. Supervised learning can be further divided into classification and regression, the first one is mostly used for discrete responses and the latter for continuous ones.
2. Unsupervised learning, which can be used to find the natural patterns, or groups, from the available data.

Here, for the particular problem at hand, we apply supervised learning, with particular focus on binary classification. This corresponds to the two possible responses we observe in preamble detection, which can be either preamble or false peak. Several methods are available from the literature, i.e., *k*-NN and naïve Bayes, supported vector machine (SVM), discriminant analysis, etc. [15].

We first consider the basic method of *k*-NN [13]. This algorithm is supposed to predict the response based on the input data. It calculates the distance between the point on a 2D plane (input) and all the remaining points (past data)

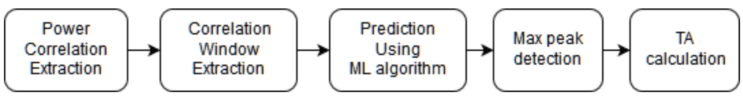

Figure 5. Multi steps detection algorithm.

and finds the nearest neighbors. The number of neighbors depends on the value of *k*. Once it chooses the nearest neighbors, it classifies the observation considering the class to which belong the majority of the neighbors. In the implementation of this method we have considered mean and variance of the power delay profile in the current detection window as input variables and preamble or false peak as the response in accordance. After collecting thousands of received preambles, we have trained our receiver using *k*-NN algorithm. The considered distance metric is Euclidean distance and we used $k = 4$. The main disadvantage of *k*-NN is the computational time, which could be an important factor in 5G since one of the main aims is that of reducing the latency. We have studied the method of decision trees classification (DTC) [17]. With the added dimension, i.e., three dimensions defined by the three predictors, the classifier showed a good response at low SNR.

The second method we implemented is naïve Bayes, which invokes the Bayes theorem

$$P(B)P(A|B) = P(B|A)P(A).$$

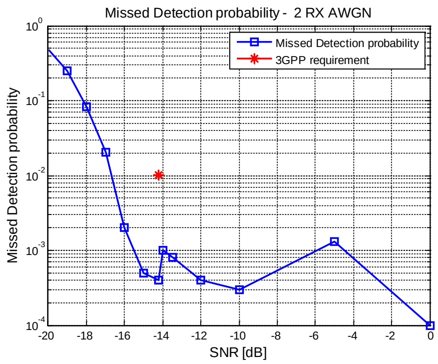

Figure 6. AWGN performance, single step receiver.

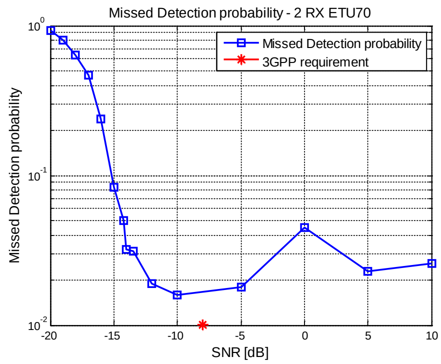

Figure 7. ETU performance, single step receiver.

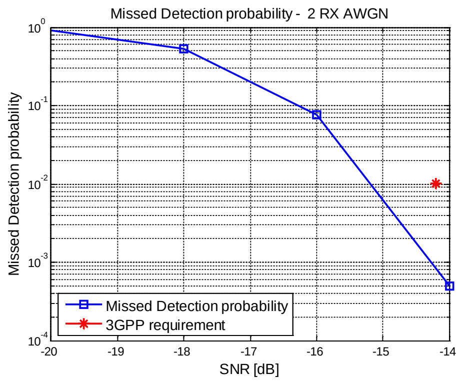

Figure 8. AWGN performance, multi-step receiver**.**

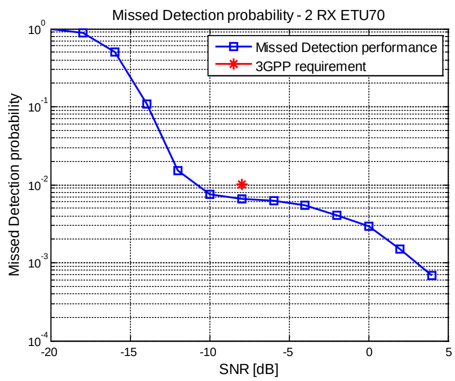

Figure 9. ETU performance, multi-step receiver.

This method is based on a fitting of the probability distribution to each class of the input data. The algorithm works on the assumption that the variables in each class are independent, which is not true in general. This algorithm calculates a posteriori probabilities of the class it belongs to for a given position. Once we have two probabilities, we then choose the maximum one. This procedure is equivalent to the maximum a posteriori (MAP) algorithm. It can be faster compared to *k*-NN and uses less storage. Also, it is more robust to noise (outliers). The modification of the receiver can be seen in Figure 5, where we introduced ML.

6. Numerical results

In this section the performance of the proposed algorithm is reported and compared with that achieved by the one step algorithm. The considered scenarios are those defined in [3]. The most relevant parameters are listed in Table 1. In what follows we do not report any result for the false alarm probability since it is below the value of 10^{-3} for both the channel scenarios, as defined in TS 36.104 [4]. The missed detection probability versus SNR for the single step detector is reported in Figure 6 and 7 for the AWGN and the ETU70 scenarios, respectively. Numerical results achieved by using the proposed multi-step detector for the same scenarios are reported in Figures 8 and 9.

Table 1. Parameters used in the simulations.

Parameter	Value
System bandwidth	20 MHZ
PRACH Format	0
Channel	AWGN/ETU70
Doppler	0/200 [HZ]
RX Antenna	2
N_{Cs}	13

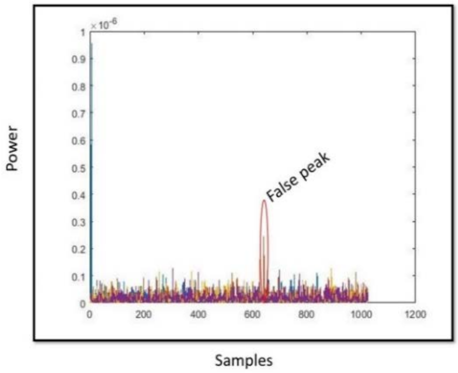

Figure 10. False peak

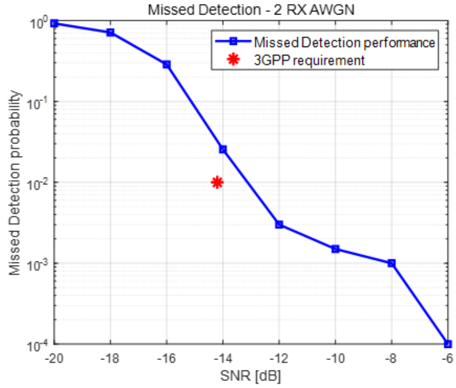

Figure 11. Performance of the PRACH 4G algorithm applied to 5G NR.

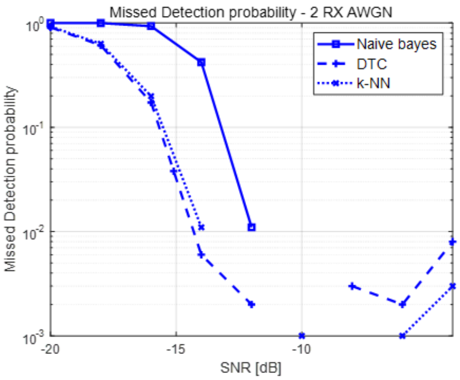

Figure 12. Performance of different classifiers for AWGN channel.

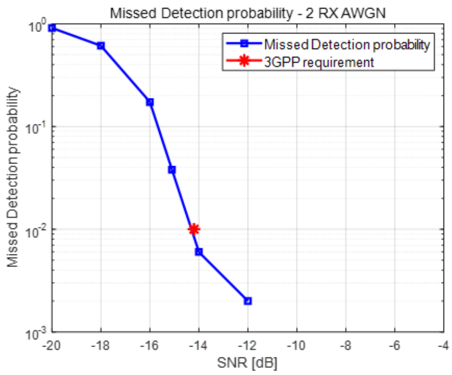

Figure 13. Performance of hybrid method for AWGN channel.

For the AWGN channel no significant differences can be observed for both the two detection algorithms. It is worth observing that a wrong selection in the design of the key factors could lead to worse performance for this scenario. Therefore, a trade-off between the two considered different scenarios must be done in the selection of the key parameters. On the other side for ETU channel, the proposed detection algorithm allows to satisfy the stringent requirements defined in [3], which is a missed detection probability lower than 1% at $\mathrm{SNR} = -14.2\,\mathrm{dB}$. Note that we have not reported results for other bandwidths because they are very similar to those we have reported here.

An issue that we found at moderate to high SNR scenarios is the detection of extra peaks (noise being detected as a preamble). This effect, which can be observed in Figure 10, is named false peak to differentiate it from the original peak corresponding to the preamble sent by the user. The simulation results obtained by applying the three steps algorithm developed for 4G to 5G are reported in Figure 11. As it can be observed the performance is far from the desired results of 99% detection probability at $\mathrm{SNR} = -14.2\mathrm{dB}$. Sometimes, it happens that our detection algorithm is not able to set a threshold to avoid peaks that are not the intended. It seems that adjusting the threshold, possibly by increasing it, is a good idea. However, the problem with this is that the false peak is not observed in every transmission time interval (TTI). Instead it appears only in certain TTIs. So, it would not be ideal to adjust the threshold, which might affect the performance at moderate SNR. Moreover, as it is a random event, it is extremely difficult to have the prior information regarding the TTI in which we might have a possible false peak. An algorithm that can differentiate the false peak from real ones is therefore needed. Among the best approaches to deal with this issue, ML algorithms seem to be the most appropriate, where the receiver can be trained to learn the behavior of this false peaks and help in differentiating them from the original ones. This would not only solve the problem of false peaks but opens the way for possible usage of ML algorithms in RAN [16]. We have tried to use Naïve Bayes [12] algorithm which show a lot of promise, especially at high SNR. We have reported the results of *k*-NN, DTC and naïve Bayes algorithms in the Figure 12. As it can be observed, the results we have obtained with *k*-NN and DTC are closer to the desired performance than those obtained by applying 4G algorithm to 5G, as shown in Figure 11. For the naïve Bayes the performance is much worse that *k*-NN and DTC at low SNR but it greatly improves at higher values of SNR. The reason of this behavior is the pattern of the collected data. The original peaks at low SNR have data points in the close proximity of the data points of the false peaks, and this leads to a lower likelihood probability *p*(position|preamble). The posterior probability *p*(preamble|position) is proportional to the probability of the likelihood [18], so it turns out to be lower at low SNR scenarios. A different behavior happens at high SNR, which is the reason why it has very good performance at high SNR. After observing the peculiar behaviors of these two classifiers, we decided to use a hybrid method, which combines *k*-NN/DTC and naïve Bayes the classifiers to obtain best possible performance. Our idea is to use either *k*-NN or DTC at low SNR and naïve Bayes at high SNR. After having observe the results we chose SNR = -10 dB, which is the crossing point of the performance of the two classifiers. The results are reported in the Figure 13.

7. Conclusion

This paper focuses on the problem of preamble detection in the PRACH signal for 5G. As a first solution we propose the extension to 5G of a three steps algorithm we designed for 4G. Since the performance is not satisfactory, especially due to the problem of false peaks, the application of a hybrid method based on the combination of two ML algorithms is considered, which are *k*-NN and naïve Bayes. Although even with the hybrid ML method we are not able to satisfy the 3GPP requirements, a considerable improvement is observed.

As a future work we intend to consider a logistic regression and compare the resulting performance with that achieved by using support vector machine, which is the ML algorithm giving the best performance. However, its use demands for more complexity and the resulting improvement of performance must be evaluated also in terms of increase of processing time.

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