Impulse Noise Detection in OFDM Communication System Using Machine Learning Ensemble Algorithms

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Abstract. An impulse noise detection scheme employing machine learning (ML) algorithm in Orthogonal Frequency Division Multiplexing (OFDM) is investigated. Four powerful ML's multi-classifiers (ensemble) algorithms (Boosting (Bos), Bagging (Bag), Stacking (Stack) and Random Forest (RF)) were used at the receiver side of the OFDM system to detect if the received noisy signal contained impulse noise or not. The ML's ensembles were trained with the Middleton Class A noise model which was the noise model used in the OFDM system. In terms of prediction accuracy, the results obtained from the four ML's Ensembles techniques show that ML can be used to predict impulse noise in communication systems, in particular OFDM.

Keywords: Ensemble, prediction, Bagging, Boosting, Stacking, Random Forest, OFDM and impulse noise.

1 Introduction

Orthogonal Frequency Division Multiplexing (OFDM) has become a popular modulation for both wireline and wireless communications. A block diagram of an OFDM system (including a ML block at the reciver) is shown in Figure 1. An OFDM system has advantages of being robust against frequency selective fading and high data rate compared to single carrier systems, due to the transmission of data in multiple frequency carriers. However, OFDM can be adversely affected by impulse noise because the energy of an impulse is spread by the FFT such that it appears distributed across all the frequency carriers at the output of the FFT [1]. It is for this reason that most impulse noise mitigation schemes on OFDM focus on reducing the effect of the impulse noise before the FFT on the receiver side of the OFDM system (see [2] and [10] for impulse noise mitigation schemes and impulse noise models). Such methods are termed clipping and/or nulling [4], [5], where thresholds are used to detect impulse noise in the time-domain and clip or null any time sample that is above the set threshold. Other impulse noise mitigation methods can be used together with the clipping/nulling scheme, for example: in [3] and [8], the authors implemented the iterative impulse noise estimation technique with clipping/nulling. In [6], [7] and [9], error correcting coding is used to combat impulse noise and it can still work together with the clipping or nulling scheme to obtain a powerful impulse noise combatting scheme.

In this paper, the focus is the clipping and/or nulling schemes using thresholds to detect impulse noise. In that regard machine learning multi-classifier or ensemble algorithms were used to estimate the amplitude (or power) of the impulse noise.

Machine learning (ML) is a subfield of artificial intelligence theory that was developed from the study of pattern recognition and computational learning theory [12]. Recently, Machine Learning algorithms have been utilised in prediction, classification, monitoring and optimisation tasks in many important applications such as medical science, engineering applications, intelligent control systems etc. [12], [13].

Ensembles or multi-classifier methods have recently become as a common learning method, not only because of their straightforward implementation, but also due to their outstanding predictive performance on practical and real-life problems [13]. An ensemble contains a set of individually trained classifiers (for example decision trees or neural networks) whose predictions are combined when classifying distinctive instances. Ensemble methods aim to improve the predictive performance of a given statistical learning or model fitting technique [13].

This work was conducted to examine the use of four popular and powerful multi-classifiers (ensembles) (Bag, Bos, Stack and RF) to predict, thus estimate impulse noise on OFDM. In this work we consider the conventional OFDM communication system employing PSK/QAM modulation as shown in Figure 1, which we call PSK/QAM-OFDM in short. The OFDM system is discussed in detail in Section II.

The ML classifiers are trained with the impulse noise statistics so that they should be able to predict the DFT samples (of OFDM) that contain impulse noise at the receiver. Once the samples with impulse noise are located using the ML classifiers, the impulse noise can be subtracted from the received signal, leaving an estimate of the transmitted signal plus additive white Gaussian noise (AWGN).

2 System Model

OFDM uses the power of the discrete Fourier transform (DFT) to transmit data in multiple frequencies as follows: Symbols from phase shift Keying (PSK) modulation or quadrature amplitude modulation (QAM) are taken as input to the OFDM transmitter. These symbols are processed by the inverse discrete Fourier transform (IDFT) at the transmitter. At the receiver side, a DFT is performed on the received symbols which would have been affected by channel noise. The PSK/QAM-OFDM system is shown in Figure 1, where the transmitter side is shown together with the transmitted signal (Tx) which is affected by additive noise (AWGN and Impulse noise) as it passes through the channel.

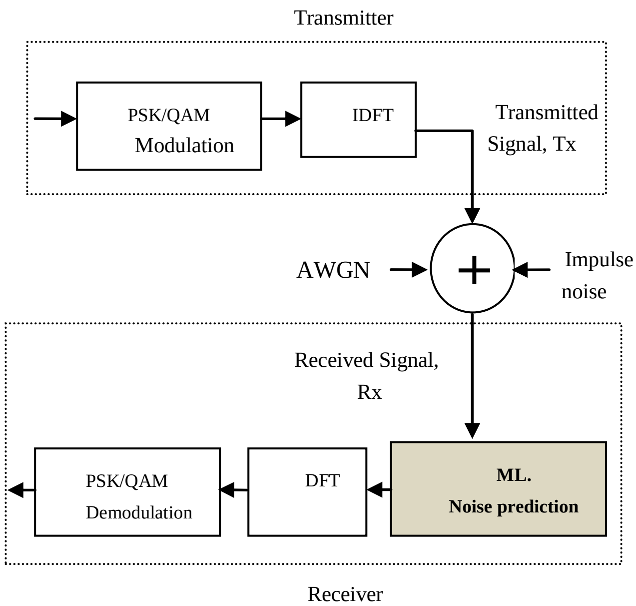

Fig. 1. OFDM communication system with Machine Learning for impulse noise estimation

The noise affected signal (Rx) is received at the receiver side for processing by the ML noise prediction tool which contains the ensemble algorithms before being fed to the DFT. The ML noise prediction tool task is to estimate the noise in the received signal and classify the signal as either containing only AWGN or impulse noise. The details of how the ML noise prediction ensemble algorithms are used to classify the noise are discussed in Section IV. For now the ML ensemble algorithms used in the prediction of noise are discussed, in the next section.

3 Multi-classifiers (Ensembles) Algorithms

3.1 Bagging

Bagging or Bootstrap aggregating (Bag) is a popular way to obtain multiple classifiers. Bag. was proposed by Breiman in 1996 to improve the classification results by merging outputs of classifiers that are trained using randomly-generated training sets [14], [15].

Bag. is a "bootstrap" multi-classifier method that produces individuals for its ensemble by training each classifier on a random redistribution of the training set. Each classifier's training set is generated by randomly drawing, with replacement, X examples, where X is the size of the original training set; many of the original examples may be repeated in the resulting training set while others may be left out [14], [15]. Each single classifier in the ensemble is generated with a different random sampling of the training set [15].

3.2 Boosting (Bos)

Bos. algorithm was proposed by Schapire and Freund [16]. Boosting comprises a family of methods. The focus of those methods is to generate a series of classifiers. The training set used for each member of the series is chosen based on the performance of the earlier classifier(s) in the series [17]. In Bos, cases that are wrongly predicted by previous classifiers in the series are chosen more often than cases that were appropriately predicted. Thus Boosting tries to create new classifiers that are better able to predict cases for which the present ensemble's performance is poor. Note that in Bag. technique, the resampling of the training set is not dependent on the performance of the earlier classifiers [15, 16, 17].

3.3 Random Forest (RF)

The Random Forest method is based on bagging (bootstrap aggregation) models built using the Random Tree method, in which classification trees are grown on a random subset of descriptors [18]. The Random Tree method can be viewed as an implementation of the Random subspace method for the case of classification trees. Combining two ensemble learning approaches, bagging and random space method, makes the Random Forest method a very effective approach to build highly predictive classification models [19].

3.4 Stacking (Stack)

Stack. is historically one of the first ensemble learning methods. It combines several base classifiers, which can belong to absolutely different classes of machine learning methods, by means of a "meta-classifier" that takes as its inputs the output values of the base classifiers [19]. Although stacking is a heuristic method and does not guarantee improvement in all cases, in many practical studies it shows excellent performance.

4 Simulations

4.1 Simulation set-up

The four machine learning ensemble techniques were used to classify thresholds of the received signals as either containing the transmitted signal, containing the transmitted plus AWGN or containing the transmitted signal plus AWGN plus impulse noise. To do this we create three classes which will be used by the four used ensemble techniques.

To set up the three thresholds (or classes) we use the following knowledge about signal transmission in an impulse noise channel. Impulse noise is usually of very high amplitude compared to the transmitted signal and AWGN. The transmitted signal is usually given a variance of one ($\sigma_s^2 = 1$) and AWGN also has a variance of one ($\sigma_g^2 = 1$). We can set the variance of impulse noise (σ_I^2) to any value greater than one. When employing the Middleton Class A noise model, it is customary to define the variance of impulse noise as function of $\sigma_g^2 = 1$, such that $\sigma_I^2 = K\sigma_g^2$, where $K > 1$. On average, we can note that the amplitude of the transmitted signal plus AWGN will be the value 2 ($\sigma_s^2 + \sigma_g^2 = 1 + 1$). Therefore we set our first threshold to cover values from 0 to 1 (T_0 = 0 - 1). The second threshold is set to cover values from 1.1 to 2.1 (T_1 = 1.1 - 2.1). The third threshold is set to be values from 2.2 and above ($T_2 \geq$ 2.2). The threshold of 2.2 was used in [8] and was shown to be effective for detecting impulse noise. Table 1 shows a summary of the different classes of the received signal.

The split to train ratio for all used classifiers was 70% to 30% of the data.

Table 1. Signal, AWGN and Impulse noise level classes

Class	Threshold Description	Numerical Threshold Level
1	Signal, T_0	0 - 1
2	Signal + AWGN, T_1	1.1- 2.1
3	Signal + AWGN + IN, T_2	> 2.2

Figure 2 illustrates the number of instances (count) and weight distribution for each class for noise classes.

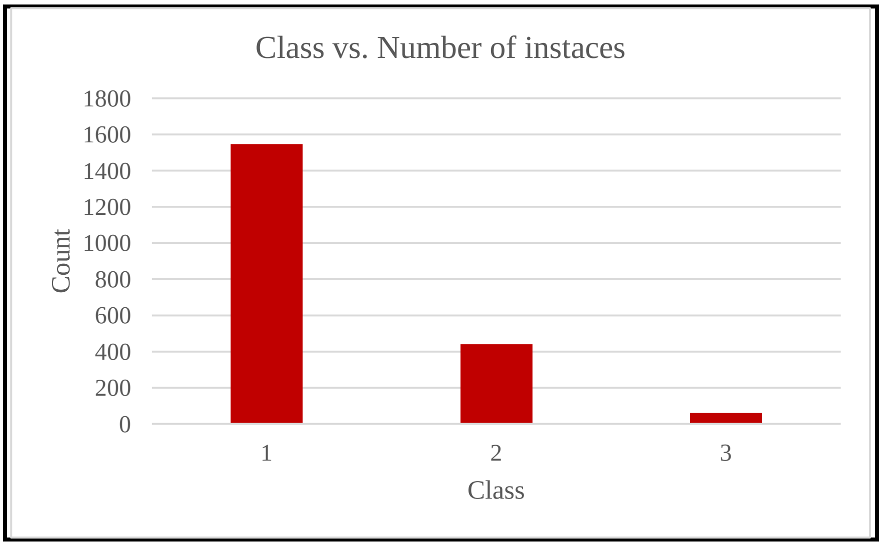

Fig. 2. Data distribution over class

It can be seen from figure 2 that 1546 instances were classified as class 1, 441 instances as class 2, and 61 instances as class 3. Almost 75% of the data were classified as class 1 which cause the data to be imbalance, however the data in this experiment were dealt with collectively using cross validation by randomly choosing 70% of the impulse noise generated data to train the classifiers and 30% to test them.

4.2 Results discussion

The main performance measure for this experiment is the prediction accuracy, however mean absolute error and root mean square error are included as a secondary performance measures to provide more statistical information about each classifier performance. MATLAB simulator was used to classify the data, using default parameters for all classifiers. The simulation results are shown in Table 2.

In terms of prediction accuracy, it can be seen from Table 2 that Bag and RF barely outperformed the other two ensemble classifiers with a 99.85% prediction accuracy. Bos and Stack also showed good performance with high prediction accuracy of 99.51%, and 97.31% respectively. In terms of the secondary performance measures, it can be noticed that Bag and RF also achieved the best performance and scored the lowest mean absolute error and root mean square error.

Table 2. Impulse noise prediction accuracies

Description	Bag	Bos	Stack	RF
Prediction accuracy	99.85%	99.51%	97.31%	99.83%
Mean absolute error	0.002	0.017	0.028	0.002
Root mean squared error	0.022	0.066	0.028	0.030

5 Conclusions

We have shown that ensemble or multi-classifiers techniques can be used for impulse noise prediction in OFDM systems affected by background noise (AWGN) and impulse noise. The results achieved from this investigation show that the Bag, RF, Stack and Bos algorithms can predict impulse noise with high level of confidence and accuracy. The four different ML's ensemble techniques were tested, and found to be effective at predicting impulse noise as Bag, Bos and RF realized more than 99.0%, and Stack achieved 97.31%. In terms of imbalanced data, this problem could be overcome by using techniques such as, re-sampling data, collecting more data. etc. The data imbalance tends to suit RF and Bagging, hence these methods could be used for predicting impulse noise. Statistically, Tukey multiple test shows that there no significant difference in performance between all classifiers.

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