Weak sinusoidal signal extraction from white noise using convolutional neural network

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***Abstract*—A great number of analog and digital data communications schemes use the sinusoidal waveform as a basic elementary signal, including the spread spectrum data exchange techniques. Detection of the presence of the sinusoidal waveform in a mixture of signal and noise is a common task, regardless the specific modulation scheme. This paper presents the machine learning-based approach for detection of the sinusoidal wave. It presents the structure of the convolutional neural network, as well as the performance metrics for the sinusoidal signals detection. The paper provides an assessment of the overall accuracy for the binary signals. It reports the overall accuracy value of 0.93 for the sinusoidal signal detection in the presence of additive white Gaussian noise at the signal-to-noise ratio value of −20 dB for a balanced dataset.**

***Keywords*—digital communications, modulation, manipulation keying, demodulation, detection, bit error rate, machine learning, deep learning, convolutional neural network, JT65**

I. Introduction

The most fundamental digital modulation techniques are based on the use of sinusoidal waveform as a carrier [1], [2]. Automatic information extraction in signal monitoring requires some intermediate steps such as modulation classification, signal identification [3], etc. Demodulation includes the estimation of sinusoidal waveform parameters, such as amplitude, phase, and frequency. This paper presents the method for detection of the presence of the sinusoidal component in the mixture of signal and noise. It can be implemented in the software-defined radios, cognitive radios, and wireless sensor networks. The presented method of the detection of the continuous sinusoidal wave is also applicable in radiotelegraphy as well as in radiolocation.

II. Related work

Paper [4] presents a novel signal extraction algorithm from chaotic background using wavelet packet transform. In [5], the authors present a new method for the detection of signals in "noise", which is based on the premise that the "noise" is chaotic with at least one positive Lyapunov exponent. A novel method of detection, extraction, and estimation of amplitude, phase and frequency of sinusoids of time-varying nature is presented in [6]. In the paper [7], the problem of non-coherent detection of a sinusoidal carrier is considered in the presence of Gaussian noise. The author of [8] investigates the convexity properties of error probability in the detection of binary-valued scalar signals corrupted by additive noise. The paper [9] solves the problem of weak radio signals demodulation for Frequency Shift Keying (FSK) and Phase Shift Keying (PSK) signals with Machine Learning (ML) using perceptron model with randomization. Paper [10] provides the bit-error-rate performance of the spread spectrum binary communication system with noise shift keying scheme using the entropy demodulation. Reference [11] presents the idea of using CNNs with deep learning structure to predict future symbols based on the received signal, to further reduce inter-symbol interference and to obtain a better Bit Error Rate (BER) performance in chaotic baseband wireless communication systems.

III. METHODOLOGY

Fig. 1 shows the time domain waveform and the spectrogram of the mixture of signal and Additive White Gaussian Noise (AWGN) at SNR −20 dB.

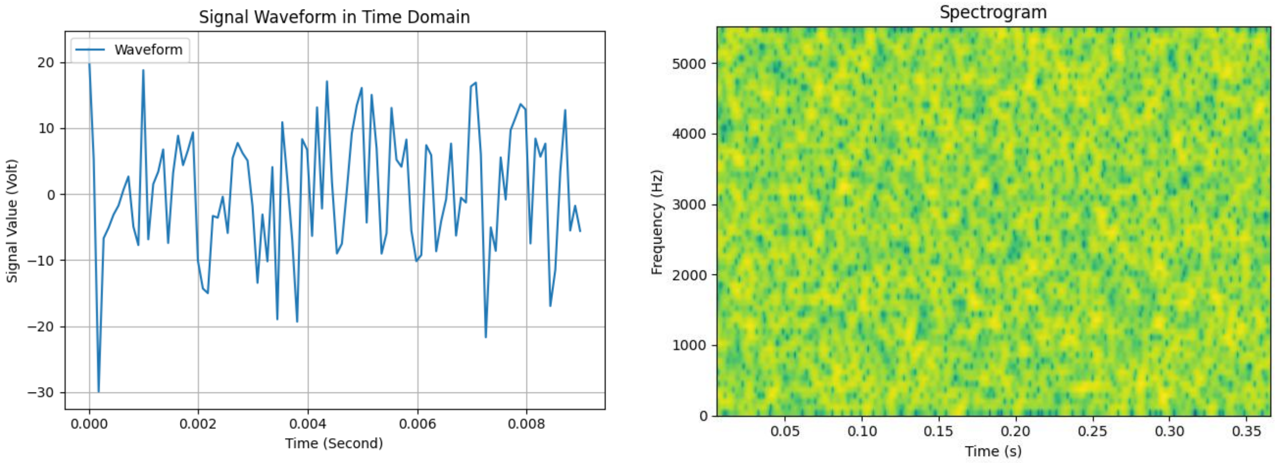

Fig. 1. Time domain waveform and the spectrogram of the mixture of signal and AWGN

Fig. 2 shows the structure of the convolutional neural network that is used for the detection.

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Layer (type)                Output Shape              Param #
=================================================================
reshape (Reshape)           (None, 4096, 1)           0
batch_normalization         (None, 4096, 1)           4
conv1d (Conv1D)             (None, 4096, 128)         2176
max_pooling1d               (None, 2048, 128)         0
dropout (Dropout)           (None, 2048, 128)         0
batch_normalization_1       (None, 2048, 128)         512
conv1d_1 (Conv1D)           (None, 2048, 64)          131136
max_pooling1d_1             (None, 1024, 64)          0
dropout_1 (Dropout)         (None, 1024, 64)          0
batch_normalization_2       (None, 1024, 64)          256
conv1d_2 (Conv1D)           (None, 1024, 32)          32800
max_pooling1d_2             (None, 512, 32)           0
dropout_2 (Dropout)         (None, 512, 32)           0
flatten (Flatten)           (None, 16384)             0
batch_normalization_3       (None, 16384)             65536
dense (Dense)               (None, 64)                1048640
batch_normalization_4       (None, 64)                256
dense_1 (Dense)             (None, 2)                 130
=================================================================
Total params: 1281446 (4.89 MB)
Trainable params: 1248164 (4.76 MB)
Non-trainable params: 33282 (130.01 KB)
```

Fig. 2. Structure of the convolutional neural network

In this research, the modulation scheme is On-Off-Keying (OOK). The main baseband frequency is 1270.5 Hz. The baseband bandwidth is 5,512.5 Hz. The sampling rate is 11,025.0 Hz. The bit duration time is 0.3715 s, 4096 samples (exactly as it is in JT65 protocol [12, 13]). The bit rate is 2.6917 bit/s. The signal-to-noise ratio (SNR) is −20 dB, the normalized signal-to-noise ratio (E_b/N_0) is +13.1 dB, and the spreading factor is +33.1 dB). The size of the training dataset is 10720 records, the validation set size is 2680, and the test set size is 6600 records. Initial training/test split ratio is 0.33; training/validation split ratio is 0.2. The loss function: sparse categorical cross-entropy, optimizer: adam. Two separate output neurons are used in the model. There is no need for one-hot encoding for labels due to the sparse loss function. The binary model can be easily converted to a multiclass classifier for m-ary signals.

IV. RESULTS

The classification report for the test data is shown in Table 1, the confusion matrix - in Table 2.

TABLE 1. CLASSIFICATION REPORT

Class	**Classification Metric**			
	Precision	Recall	F1-Score	Support
0 – "space"	0.89	0.98	0.93	3351
1 – "mark"	0.97	0.87	0.92	3249
Accuracy			0.93	6600
Macro avg	0.93	0.93	0.93	6600
Weighted avg	0.93	0.93	0.93	6600

TABLE 2. CONFUSION MATRIX

True	**Predicted**		
	0	1	All
0	3273	78	3351
1	410	2839	3249
All	3683	2917	6600

V. DISCUSSION

The purpose of this study was to gain a better understanding of the ability of machine learning algorithms to detect the baseband sinusoidal signals. The result of the present study supports the hypothesis that the presence of sinusoidal signal can be detected with ML techniques. The results of this research provide supporting evidence that it is possible even in the presence of noise. This is the main take away from this paper. This pattern of results is consistent with our previous works those deal with ML-based demodulation for frequency shift keying modulation scheme. These results represent the direct demonstration of sinusoidal signal detection within the scope of the ML approach. There are at least three potential limitations concerning the results of this study. A first limitation is that we used signals generated with the same power. A second potential limitation is that we used supervised machine learning approach. This means that the algorithm should be trained on previously known data. Unsupervised approach looks like more promising technique. The third limitation is that we considered only the case of AWGN interference. Despite these limitations, the results suggest practical implication that sinusoidal signals can be detected using ML.

VI. FUTURE RESEARCH

In terms of future research, it would be useful to use the quantum optimization algorithms [14]. The results might be applied in data communication applications in mobile robotics [15]. Also, it would be useful to research the ability of unsupervised ML [16] approach in the context of this task. Other types of interferences (chaotic [4, 5], intermodulation distortion [17], etc.) should be studied as well.

VII. CONCLUSION

The main conclusion that can be drawn is that sinusoidal baseband signals can be detected using supervised machine learning approach. In summary, this paper presents the values of quality metrics. The overall accuracy 0.93 and minimum F1-score is 0.92 at SNR value of −20 dB.

VIII. ACKNOWLEDGMENT

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IX. ETHICS DECLARATIONS

The author has nothing to disclose.

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