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A Robust Feature-Based Approach for Recognition of Line Coding Schemes

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ABSTRACT Decoding communication signals in a non-cooperative environment has always been a challenging task. Even after the estimation of various transmission-related parameters, the unknown received signal still cannot be decoded without the correct classification of the incorporated line coding scheme. In this paper, a robust short-sample feature-based approach is presented which recognizes line coding schemes in a sequential manner by an in-depth examination of linked characteristic features. The proposed approach provides an overall correct classification accuracy higher than 90 percent with an input of just 13 bit-waveforms whereas perfect classification accuracy (100 percent) is achieved with just 30 bit-waveforms of the unknown received signal. A detailed comparison considering noiseless as well as noisy channel environment is also carried out vis-à-vis existing approach based on extensive simulation results. Additionally, the paper bridges the gap between theory and simulations to justify the obtained accuracy results for conventional line codes under consideration. The substantial increase in classification accuracy for a smaller number of input bit-waveforms shall aid effective decoding of the unknown received signal even at the initial stages of reception. In general, it can benefit many practical spectrum surveillance applications, where proactiveness is paramount.

INDEX TERMS Line codes, short-sample recognition, characteristic features, feature-based approach.

I. INTRODUCTION

The process of encoding a digitized message signal using electrical waveforms for transmission over the channel is commonly referred as line coding. Various line coding schemes have been introduced for different transmission environments [1]–[3]. The desirable attributes of line code schemes include, small transmission bandwidth, power efficiency, built-in error detection and correction capability, noise immunity, favorable power spectral density (zero dc value), self-synchronization and transparency [4]. Due to these advantageous properties linked to the line codes, it is mostly certain for a message signal to be encoded with a particular line coding scheme before transmission. Technical standards such as Inter-Range Instrumentation Group (IRIG) [5], have regulated the use of conventional line coding schemes for telemetry and telecommand signals. These conventional schemes include unipolar, polar, bipolar and Manchester signaling.

Fast decoding of telemetry, telecommand and telecommunication signals in a non-cooperative environment is recognized as a pivotal source of information for undertaking timely precautions against unforeseen circumstances. The information signal intercepted in a non-cooperative context shall not contain transmission related parameters required by the receiver for decoding purposes. Therefore, estimation of transmission parameters is the only viable solution.

Several methods for estimation of various transmission related parameters have sprung up in the recent past. In [6]–[10], likelihood-based methods for recognition of digital modulation techniques are discussed whereas feature-based methods identifying different modulation schemes using respective characteristic constellations are presented in [11]–[15]. A survey of modulation classification methods based on both traditional approaches is covered in [16]. Classification of channel codes in a non-cooperative

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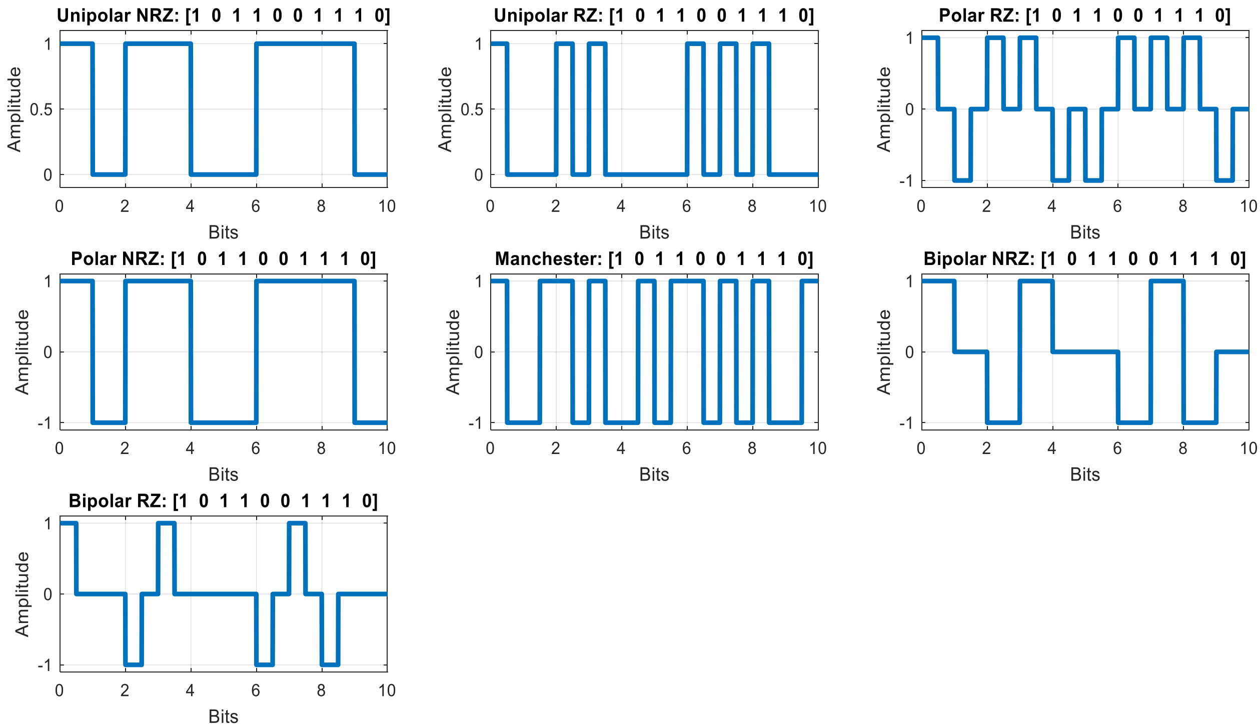

FIGURE 1. **Plots of conventional line coding schemes for an arbitrarily selected 10-bits binary sequence. It can be clearly seen that unipolar signaling has no negative polarity present in the signal, whereas Manchester and polar NRZ lacks the presence of zero signal level. The maximum possible count of consecutive high, zero, and low constant level minimum intervals can also be visualized for each scheme by closely observing the nature of the respective encoded signal.**

context is discussed in [17], [18], and particularly, recognition of space-time block codes and turbo codes is presented in [19], [20] and [21], [22], respectively. Blind estimation of interleaver parameters has been addressed in [23]–[26], moreover, methods to estimate convolutional and block interleaver parameters are discussed in [27]–[30] and [31], [32], respectively.

It is pertinent to highlight here that even after the estimation of various transmission-related parameters discussed above, the unknown received signal still cannot be decoded without the correct classification of the incorporated line coding scheme. Moreover, early extraction of hidden information in the unknown received signal, which is of crucial importance for the performance of many spectrum surveillance applications, demands from these classification / estimation algorithms to not only be accurate but fast as well. To the best of our knowledge, research specific to classification of line coding schemes is still a pending task. No literature except [33] (discussed later) is available in this regard. This paper therefore contributes to this field by proposing a robust approach to recognize conventional line coding schemes using relevant characteristic features. Our classification algorithm takes unknown received signal as input and identifies the incorporated line coding scheme in a sequential manner based on short-sample bit waveform characteristic features.

The main contributions of our work are summarized below:

1. A robust feature-based approach is proposed to recognize conventional line coding schemes with an aim to assist effective decoding of unknown received signal at initial stages of reception.
2. The shortcomings of the most recent related approach presented in [33] are first highlighted and subsequently resolved using simple but effective techniques.
3. Classification accuracy with respect to received number of unknown bit-waveforms in noiseless as well as noisy environment is recorded and analyzed using extensive simulation-based results.
4. The theoretical foundation behind the obtained simulation-based classification accuracies is established in order to show coherence between theory and simulations.
5. Our proposed approach outperformed the existing state-of-the-art algorithm by achieving perfect classification accuracy with significantly reduced number of input bit-waveforms of the unknown received signal.

II. RELATED WORK

The only existing state-of-the-art approach with regards to feature-based classification of line codes is given in [33], where Janghoon Oh *et al.* have presented a sequential classification algorithm, which classifies conventional line coding schemes based on characteristic features. The algorithm achieves a correct classification probability higher than 90 percent, provided, more than 30 bit-waveforms of the unknown signal are received. Our feature-based approach proposed in this paper is inspired by the work presented in [33].

The rest of the paper is organized as follows; Section 3 briefly presents the details of classification algorithm presented in [33]. Section 4 explains the proposed approach. Section 5 describes the methodology used for evaluation whereas Section 6 carries out detailed comparison between both approaches by highlighting the obtained results. Finally, Section 7 offers conclusion.

III. PREVIOUS APPROACH

In [33], four characteristic features inherent to respective line codes have been utilized in order to classify conventional line coding schemes. All conventional schemes based on polar, unipolar, bipolar and Manchester signaling along with their Non-Return-to-Zero (NRZ) and Return-to-Zero (RZ) variants are considered for classification purposes. Fig. 1 refers to the signal dynamics for each of the respective line coding scheme considering an arbitrarily selected same binary sequence. The simplest of all is the unipolar / on-off scheme which represents bit 1 as a high voltage pulse (>0) and bit 0 with zero signal level or no pulse. The polar scheme encodes bit 1 same as the unipolar case but bit 0 as a low voltage pulse (<0). With equally likely bit states (1 or 0) in the message signal, the power of DC component in polar signaling is zero. When polar signaling is used with modified pulse shapes which encode bit 0 and 1 with low to high and high to low voltage transitions, respectively, with a zero crossing at half of pulse width, the resulting signal is known as Manchester line code. Besides zero DC component, it provides valuable information for receiver bit synchronization irrespective of bit states. Finally, the bipolar scheme also known as alternate mark inversion (AMI) encodes bit 0 as no pulse and bit 1 as an alternating high or low voltage pulse based on whether the pulse representing preceding bit 1 is of the low or high voltage, respectively. The characteristic features of the above discussed conventional line codes include:

A. PULSE POLARITY

This feature detects the presence of negative polarity in the unknown received signal. As unipolar signaling does not incorporate negative polarity in the transmitted signal, thus this feature distinguishes unipolar signaling from rest of the conventional schemes.

B. DETECTION OF ZERO LEVEL

The feature is responsible for identifying schemes that incorporate zero amplitude level in the message signal. As by design virtue, polar NRZ and Manchester scheme does not incorporate zero signal level, hence both of these schemes can be separated from others using this simple feature.

C. NUMBER OF CONSECUTIVE CONSTANT LEVEL MINIMUM INTERVAL (CLMI)

This feature counts the maximum number of consecutive high constant level minimum interval (CLMI) and zero constant level minimum interval (CLMI) present in the unknown received signal. As the count for maximum possible consecutive high CLMI for the message signal incorporated with Manchester signaling cannot exceed 2, hence this feature assists in distinguishing the already separated group of Manchester and polar NRZ line coding schemes. Similarly, the count for maximum possible consecutive zero CLMI provides distinctiveness to certain line codes which results in ease of identification of that particular scheme using the unknown received signal only.

TABLE 1. Characteristic features of conventional line coding schemes.

Schemes	Negative Polarity	Zero Level	No of Consecutive high CLMI (zero CLMI)	$PAPR^{-1}$
Unipolar NRZ	No	Yes	≥0 (≥0)	0.5
Unipolar RZ	No	Yes	1 (>0)	0.25
Bipolar NRZ	Yes	Yes	1 (≥0)	0.5
Bipolar RZ	Yes	Yes	1 (>0)	0.25
Polar NRZ	Yes	No	≥0 (N/A)	1
Polar RZ	Yes	Yes	1 (1)	0.5
Manchester	Yes	No	≤2 (N/A)	1

D. PEAK-TO-AVERAGE-POWER-RATIO (PAPR)

PAPR is the ratio of peak power to average power. It depends on the number of 1's (marks) and 0's (spaces) present in the signal which makes this feature a probabilistic one in contrast to deterministic features discussed above. Intuitively, the probability that PAPR value for RZ and NRZ pulse becomes equal is approximately negligible. Hence this feature can be utilized to distinguish RZ and NRZ sequences of the same signaling source. It therefore assists in differentiating respective RZ and NRZ counter parts of unipolar and bipolar signaling.

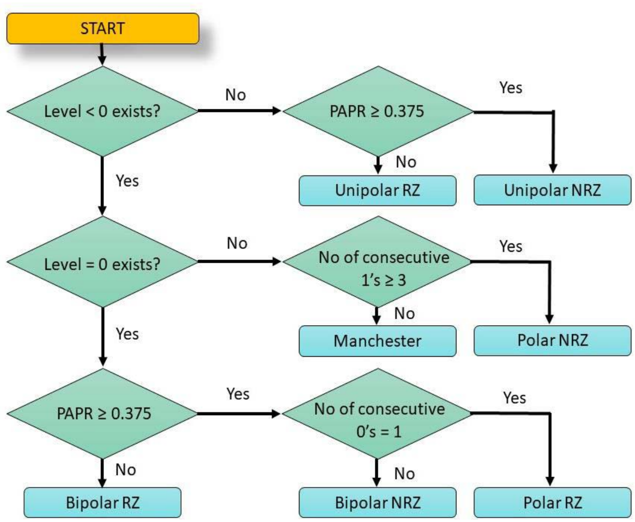

FIGURE 2. Block diagram of algorithm presented in [33] for classification of conventional line coding schemes.

The features discussed above are consolidated in Table 1. Each one of the four features are computed for all conventional line coding schemes, respectively. The first three features are generic and deterministic, no matter what binary sequence the input signal carries as can be validated using plots in Fig. 1. The last feature is probabilistic in nature and computes the inverse of respective PAPR value which normalizes the output between 0 and 1, thus, rendering the extracted PAPR feature independent of the amplitude, the received signal carries. The values of PAPR depicted in Table 1 are for a message signal with a mark ratio of 0.5. Thus, these values may change depending upon the change in 1's and 0's the message signal carries.

The sequential algorithm presented in [33] is shown in Fig. 2. It takes the received unknown signal as input and carries out the pulse polarity check. If no negative signal polarity is found in the message signal, then it distinguishes between unipolar RZ and NRZ signaling based on PAPR threshold. In case negative pulse polarity is present, then the input is checked for the presence of zero signal level. If no zero amplitude is found, then Manchester and polar NRZ schemes can be separated by counting the maximum number of consecutive high CLMI, which in Manchester case cannot exceed 2. Lastly, if both the checks above are true then the search is narrowed down to remaining three choices that include bipolar RZ and NRZ along with polar RZ scheme. The algorithm distinguishes between bipolar RZ and NRZ sequences based on PAPR threshold as discussed, whereas polar RZ is separated using the count for maximum number of consecutive zero CLMI which is always equal to unity for this scheme. The $PAPR^{-1}$ threshold for distinguishing the unipolar and bipolar RZ / NRZ counter parts, respectively, is modestly assumed in [33] to be 0.375 which is the median of the PAPR values depicted against these schemes in Table 1.

The algorithm presented in [33] achieves classification accuracy higher than 90 percent, provided that more than 30 bit-waveforms of the unknown signal are received. The results shall be further discussed in Section 6.

IV. PROPOSED APPROACH

In the previous approach, unipolar RZ and NRZ schemes were distinguished based on PAPR threshold which is a probabilistic parameter. The authors in [33] have reported no unique difference information between these schemes considering the first three robust features due to which they had to rely on probabilistic PAPR value for distinguishing purposes. As correct classification probability using robust features is bound to be better than when using probabilistic features, hence the classification accuracy of RZ and NRZ schemes for unipolar and bipolar signaling, suffered a lag period in convergence which demanded a greater number of input bit-waveforms (discussed later). If we observe closely the nature of signal in case of unipolar RZ signaling as shown in Fig. 1, it can easily be visualized that the count of maximum number of consecutive high CLMI in the received signal can never exceed unity. This is because the RZ pulse has to return to zero level before initiating response for the subsequent message bit. Thus, irrespective of the binary sequence contained in the message signal, the pulse has to return to zero after representing the respective message bit. This insight proved to be very useful, as unlike [33] it has given us the opportunity to separate unipolar RZ and NRZ schemes based on the robust feature of *No of consecutive high CLMI* instead of the probabilistic PAPR value.

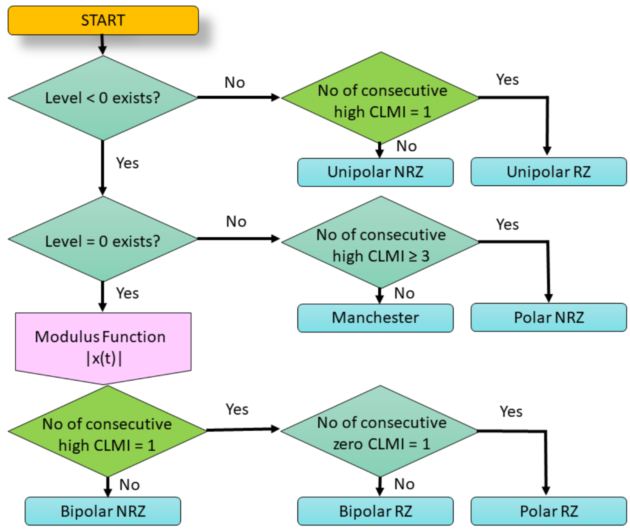

FIGURE 3. Block diagram of proposed robust recognition algorithm.

In order to disassociate the bipolar RZ and NRZ counterparts from PAPR threshold-based discrimination we have here exploited the inherent relationship between bipolar and unipolar schemes which allows us to convert a bipolar encoded signal to a unipolar encoded signal just by applying a simple absolute value or modulus function. The modulus function provides the non-negative value of signal amplitude irrespective of the sign it carries which enables us to adopt same discrimination standards for separating bipolar NRZ and RZ schemes as declared for the unipolar case. Thus, the absolute valued bipolar NRZ and RZ schemes can now be distinguished using the characteristic feature of *No of consecutive high CLMI*.

The proposed robust classification algorithm is shown in Fig. 3. The algorithm operates in a similar manner as in [33], except now the unipolar and bipolar cases are distinguished based on robust feature of *No of consecutive high CLMI* instead of probabilistic PAPR value. Thus, the proposed algorithm is less volatile in nature. The results obtained using the proposed robust classification approach for conventional line coding schemes depicted a significant improvement in correct classification probabilities of unipolar and bipolar signaling. This resulted in an overall increase in classification accuracy even for short-sample of received signal bit-waveforms. The details of the obtained numerical and simulation results along with comparisons are presented in Section 6.

As discussed earlier our approach distinguishes unipolar counterparts using the feature of *No of consecutive* *high CLMI*. We have also already established that there is no possibility for the existence of consecutive high CLMI in the received signal encoded with unipolar RZ scheme. Our algorithm checks for the presence of consecutive high CLMI in the received signal and then classifies the underlying line code as appropriate. Although the algorithm is classifying the line code as unipolar / bipolar RZ in the absence of consecutive high CLMI, there still exists the probability of misclassification for the cases where the received signal is encoded with unipolar / bipolar NRZ scheme and contains no consecutive bits. In short, we are interested in finding the probability of consecutive high CLMI in the signal with respect to the received number of bit-waveforms. This will assist us in theoretically validating the classification accuracy of the proposed algorithm.

Suppose we have N received signal bits and we are interested in the probability of consecutive ones, $P(\mathrm{N})$. We shall be adopting a reverse approach in which we initially will work our way to find the probability of no consecutive ones, $P^*(\mathrm{N})$, in a N-bit sequence, which will subsequently lead us to the desired probability. It is well-known that a set containing N-bit sequences and avoiding consecutive ones is enumerated by generalized Fibonacci sequence, [34]–[36], given as

$$F_{\mathrm{N}} = F_{\mathrm{N}-1} + F_{\mathrm{N}-2}, (\mathrm{N} > 2). \tag{1}$$

Basically, the cardinality of the set containing binary strings of length N with no consecutive ones follows the same recursive relation as of Fibonacci sequence. This can easily be proved as follows.

Consider $S_k(\mathrm{N}-1)$ to be the count of binary sequences of length $\mathrm{N}-1$ without consecutive ones and starting with k, where $k \in \{0, 1\}$. Then, the total count of $\mathrm{N}-1$ bit sequences without consecutive ones can be given as

$$S(\mathrm{N}-1) = S_0(\mathrm{N}-1) + S_1(\mathrm{N}-1).$$

Utilizing the binary tree in Fig. 4, it can be observed that the count of binary strings of length N which contain no consecutive ones and with left-most bit 1, exactly equals the count of preceding binary sequences of length $\mathrm{N}-1$ without consecutive ones but with 0 as the initial digit. Similarly, the count of N-bit sequences starting with 0 but without consecutive ones, exactly equals the total count of preceding $\mathrm{N}-1$ bit sequences without consecutive ones. This can mathematically be written as,

$$S_1(\mathrm{N}) = S_0(\mathrm{N}-1) \tag{2}$$
$$S_0(\mathrm{N}) = S_0(\mathrm{N}-1) + S_1(\mathrm{N}-1) = S(\mathrm{N}-1) \tag{3}$$
$$S(\mathrm{N}) = S_0(\mathrm{N}-1) + S(\mathrm{N}-1) \tag{4}$$

where (4) is obtained by adding (2) and (3). Using (3), we can write $S_0(\mathrm{N}-1) = S(\mathrm{N}-2)$, which can be substituted in (4) to get the desired recursive relation same as (1).

$$S(\mathrm{N}) = S(\mathrm{N}-1) + S(\mathrm{N}-2), (\mathrm{N} > 2) \tag{5}$$

From Fig. 4, we have two outcomes with no consecutive ones for $\mathrm{N} = 1$ whereas for $\mathrm{N} = 2$ we have three such

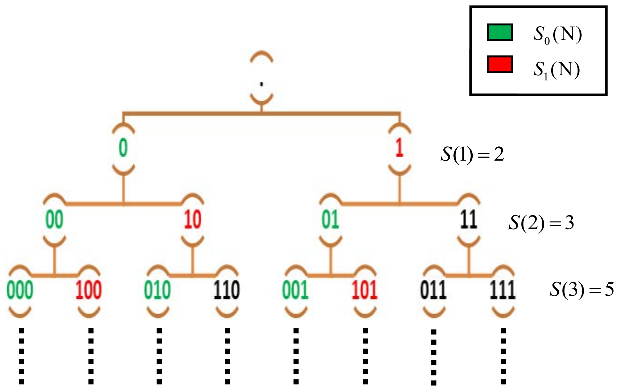

FIGURE 4. Binary tree for N > 0, where each subsequent level is obtained by prefixing 0 and 1 respectively, to the outcomes of preceding level.

outcomes out of $2^{\mathrm{N}} = 4$ total possibilities in the sample space and so on in accordance with (5). Thus, looking at the Fibonacci sequence (1, 1, 2, 3, 5, 8, 13 ...), we can say that the number of outcomes without consecutive ones for a N-bit sequence essentially equals $(\mathrm{N}+2)^{th}$ Fibonacci term. The generalized expressions for the probability of no consecutive ones in a N-bit sequence, and the desired probability of consecutive high CLMI can then be given as

$$P^*(\mathrm{N}) = \frac{F_{\mathrm{N}+2}}{2^{\mathrm{N}}}$$

and

$$P(\mathrm{N}) = 1 - P^*(\mathrm{N}), \tag{6}$$

respectively.

V. EVALUATION METHODOLOGY

To evaluate our algorithm's performance, we simulated random bit sequences, where each bit can be equally likely 1 or 0. Each randomly generated bit sequence was represented using conventional line codes under consideration. These line coded signals were then individually given as input to the proposed algorithm to obtain classification results in a non-cooperative context. In principle, without the knowledge of bitrate associated with the incoming unknown signal, it is not possible to recognize the presence of *consecutive* high, low, or zero CLMI's. Due to this limitation, a normalized unit bitrate was assumed for the entire evaluation process.

To facilitate performance comparison with existing approach in [33], we varied the number of bit-waveforms in the simulated signal from 5 to 100 with a step size of 5 for noiseless environment. Secondly, to analyze the performance of the proposed approach in noisy environment, we incorporated additive white Gaussian noise (AWGN) in the incoming unknown signal and assumed a fixed number of received bit-waveforms to only focus on evaluating classification performance vis-à-vis signal-to-noise-ratio (SNR). Lastly, we set high and low CLMI values of the input signal as 1 and -1, respectively and adopted thresholding with $\varepsilon = 0.5$ for initial signal-level decision in noisy channel environment as

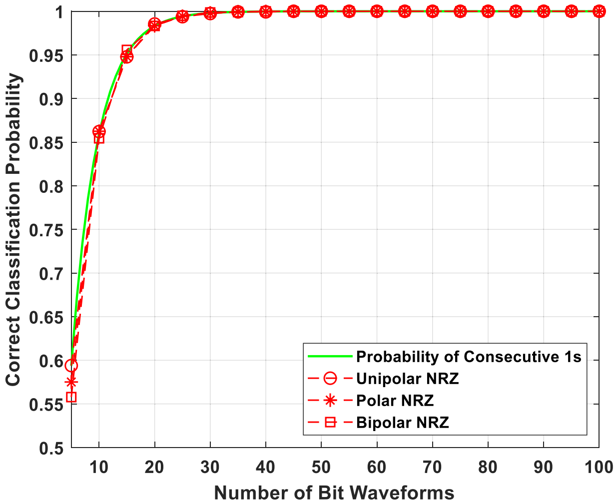

FIGURE 5. Simulation results highlighting the correct classification probability using the proposed approach for the conventional NRZ schemes versus the theoretically derived probability of consecutive 1s.

given by

$$\left\{ \begin{array}{ll} \text{level} = 1, & 1 - \varepsilon < x(t) \leq 1 + \varepsilon \\ \text{level} = 0, & -\varepsilon \leq x(t) \leq \varepsilon \\ \text{level} = -1, & -1 - \varepsilon \leq x(t) < -1 + \varepsilon \end{array} \right\}.$$

During the entire evaluation process, the correct classification probability was recorded using Monte-Carlo simulations involving 100,000 iterations.

VI. RESULTS AND COMPARISON

Intuitively, P(N) derived in Section 5 shall directly dictate the correct classification probability of the proposed algorithm in case of NRZ signaling. This is because the algorithm relies on the presence of consecutive ones in received signal to separate the NRZ scheme from its RZ counterpart. We simulated the conventional NRZ schemes (unipolar, bipolar and polar) following the evaluation methodology discussed in previous section. Fig. 5 highlights the simulation results in combination with the theoretical results given in (6). As all the curves are strictly following each other, thus, the coherence between the theoretical and simulation results has been established which justifies the classification accuracy achieved by our proposed algorithm.

Next, to carry out detailed performance comparison, the previous and proposed algorithms presented in Fig. 2 and Fig. 3, respectively were validated under same noiseless test scenario using again comprehensive Monte-Carlo simulation results involving 100,000 iterations as shown in Fig. 6. The graphs clearly highlight the substantial improvement in classification accuracy introduced by the proposed algorithm. The unipolar and bipolar NRZ schemes which previously required more than 100 bit-waveforms are now converging to 100 percent accuracy with just 30 bit-waveforms of the unknown signal. This significant increase in terms of classification accuracy is credited to the disassociation of these schemes from the PAPR based probabilistic feature for distinguishing purposes. Moreover, the unipolar RZ signaling is offering a perfect classification accuracy with just 5 signal waveforms. This is because, the proposed algorithm shall classify the underlying line code as unipolar RZ, only if no consecutive ones are present in the received signal, which shall always be the case if the signal is encoded with the RZ scheme. The Manchester and polar signaling have shown a classification accuracy approximately similar to previous algorithm as no change in the classification procedure of these schemes has been introduced in the proposed algorithm.

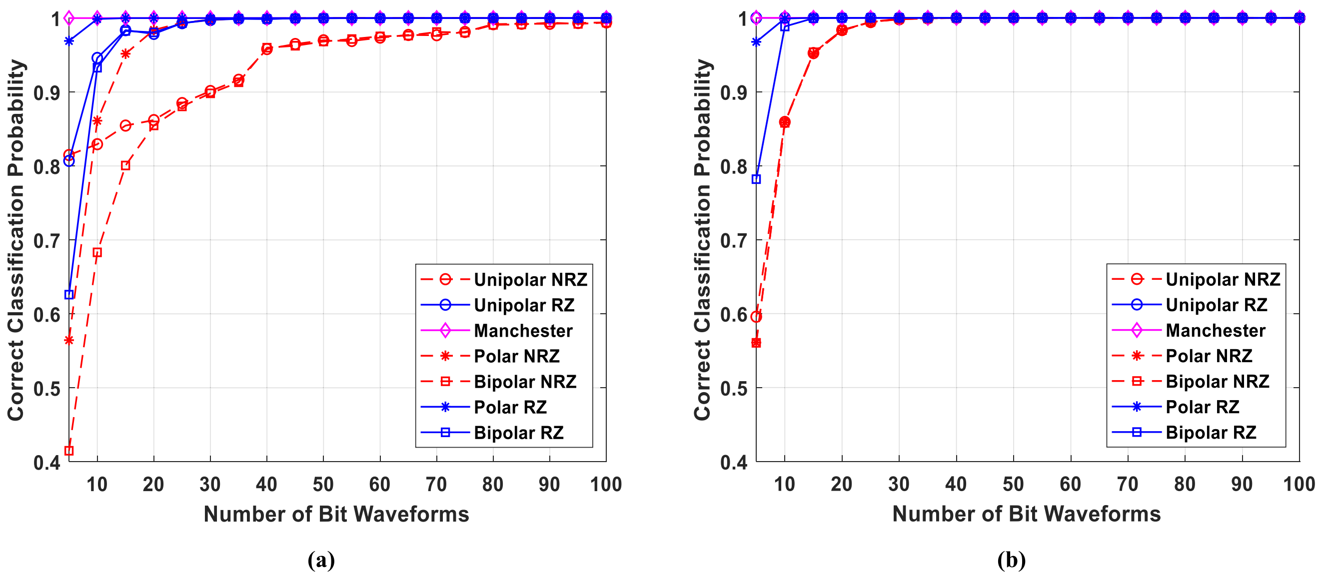

FIGURE 6. Estimated correct classification probability over 100,000 iterations of Monte-Carlo simulations versus received number of bit-waveforms in a noiseless environment. The number of input bit-waveforms is varied from 5 to 100 with a step size of 5. Common legends have been assigned to each conventional line coding scheme in both graphs for ease of comparison: (a) Previous approach, (b) Proposed approach.

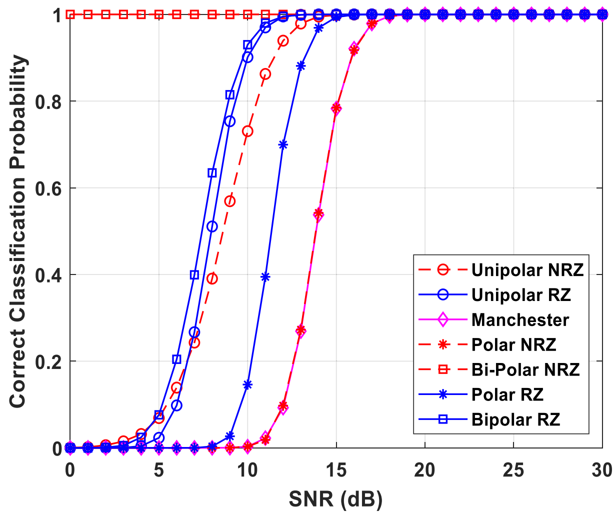

FIGURE 7. **Correct classification probability vis-à-vis signal-to-noise-ratio (SNR) for 50 input bit-waveforms considering AWGN channel.**

Thus collectively, the proposed approach offers an overall classification accuracy higher than 90 percent for all conventional line coding schemes with the intake of just 13 or more signal bit-waveforms as compared to more than 30 bit-waveforms required by the previous approach presented in [33]. It is pertinent to highlight here that the previous approach required more than 100 bit-waveforms for perfect classification accuracy (100 percent), which the proposed approach offers in just 30 bit-waveforms of the unknown received signal, thus, three to four times more efficient than its predecessor.

In case of noisy channel environment, subsequent to the signal-level decision using thresholding criterion defined in previous section, the classification of conventional line codes can be carried out using the noiseless framework already discussed in Section 4. We recorded accuracy statistics with respect to SNR for an input signal encompassing 50 bit-waveforms and passing through an AWGN channel as shown in Fig. 7. In comparison to [33], where the correct classification probability for unipolar and bipolar NRZ signaling considering 50 input bit-waveforms resulted into convergence around 0.97 even in the high SNR region (>25 dB) due to PAPR based separation, the proposed approach achieves perfect classification accuracy for all conventional line coding schemes considering same number of bit-waveforms with a significantly lowered SNR of 18 dB. However, the graph also highlights that decreasing the received signal SNR degrades the performance of the proposed approach, thereby the classification accuracy is very limited under a noisy channel environment. Due to this, the prerequisite of a good SNR value (>15 dB) for the unknown received signal can be viewed as a limitation for achieving high classification accuracy using the proposed approach.

VII. CONCLUSION

In this paper, a robust short-sample feature-based approach for recognition of conventional line coding schemes is proposed which showed significant improvement in classification accuracy with respect to received bit-waveforms. By highlighting the characteristic difference in unipolar NRZ and RZ schemes, the paper initially addressed the convergence lag issue of classification probability, encountered by unipolar and bipolar NRZ schemes in the existing approach due to PAPR based separation. The highlighted difference acted as sufficient evidence for rejecting probabilistic PAPR feature as a potential candidate for distinguishing unipolar and bipolar signaling. Revealing the inherent relationship based on modulus function between unipolar and bipolar signaling allowed for the mutual sharing of the already established short-sample classification procedure among these sister schemes. The performance of existing and proposed approaches was subsequently put through validation process using extensive simulations under same test scenario. Significant improvement in the overall classification accuracy with respect to the received number of input bit-waveforms was observed for all targeted line coding schemes considering both noiseless and noisy environments, respectively.

The substantial increase in classification accuracy for smaller number of bit-waveforms shall aid effective decoding of the unknown received signal even at the initial stages of reception. Early extraction of the information contained inside the unknown received signal can provide an unparalleled edge to many practical spectrum surveillance applications where split-second decisions matter.

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