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Visalakshi Ramakonar
Edith Cowan University

Daryoush Habibi
Edith Cowan University, d.habibi@ecu.edu.au

Abdesselam Bouzerdoum
Edith Cowan University

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CLASSIFICATION OF BANDLIMITED FSK4 AND FSK8 SIGNALS

Vis Ramakonar, Daryoush Habibi, Abdesselam Bouzerdoum
School of Engineering and Mathematics
Edith Cowan University
Joondalup, WA 6027
Australia
Email: vis@hades.fste.ac.cowan.edu.au

ABSTRACT

This paper compares two types of classifiers applied to bandlimited FSK4 and FSK8 signals. The first classifier employs the decision-theoretic approach and the second classifier is a neural network structure. Key features are extracted using a zero crossing sampler. A novel decision tree is proposed and optimum threshold values are found for the decision theoretic approach. For the neural network, the optimum structure is found to be the smallest structure to give 100% overall success rate. The performance of the both classifiers has been evaluated by simulating bandlimited FSK4 and FSK8 signals corrupted by Gaussian noise. It is shown that the neural network outperforms the decision-theoretic approach particularly for SNR < 10dB.

1 INTRODUCTION

Modulation identification plays an important part in both covert and overt operations. The main aim in communication intelligence (COMINT) applications is the perfect monitoring of the intercepted signals. The modulation type of the intercepted signal is one of the parameters that affects perfect monitoring.

Modulation classification has recently attracted interest from both the military and commercial sectors due to its capability of replacing several receivers with one universal receiver. This has practical application for example in a network environment where it is required for an incoming signal to be routed to an appropriate processor.

An automatic modulation classifier is a system that automatically identifies the modulation type of the received signal given that the signal exists and its parameters lie in a known range [1].

There have been numerous publications concerning many techniques for automatic modulation classification of digital signals in literature. Significant contributions in the area of automatic modulation classification have been made by Nandi and Azzouz [2], [3] and [4]. They propose a digital modulation recogniser that can classify ASK2 (amplitude shift keying), ASK4, PSK2 (phase shift keying), PSK4, FSK2 (frequency shift keying) and FSK4 signals. Two algorithms for modulation classification have been presented. The first technique is based on the decision-theoretic (DT) approach and the second method is a neural network (NN) implementation. The same signals have been addressed by Ramakonar et al using a DT approach in [6] and a NN implementation in [7]. However new key features were proposed and the addition of an MSK signal gave rise to a different tree structure. The NN structure was also improved for greater training efficiency.

In practice transmitted signals are bandlimited. Restricting the bandwidth of the signal, particularly an MFSK signal, will make discrimination difficult using the previously mentioned techniques in [2], [3], and [4]. Therefore this paper addresses a technique to distinguish between FSK4 and FSK8 signals based on a zero crossing method. Classification is performed using the DT approach as well as a NN approach and the results from both algorithms are compared.

2 ZERO CROSSING TECHNIQUE

A modulation recogniser that involves a zero crossing sampler as a signal conditioner is proposed by [1]. The classifier is designed for constant envelope signals such as carrier wave (CW), MPSK and MFSK. The classification strategy consists of two major steps. First the received signal is classified as either single tone (CW or MPSK) or MFSK. The second step is to make a decision based on the number of detected states. However, when the signal is bandlimited, the number of detected states becomes hard to determine for MFSK signals. This gives rise to the proposed modified method.

The received waveform is modelled as

$$r(t) = s(t) + v(t), \quad 0 \le t \le T_o \tag{1}$$

where $s(t)$ is a constant envelope modulated signal with unknown modulation type. T_o is the observation interval and $v(t)$ is an additive bandlimited Gaussian noise with zero mean and autocorrelation function $\varphi(\tau)$.

Time tags of zero crossing points are recorded to form a zero crossing sequence $\{x(i), i = 1,2,\ldots,N\}$ as the received signal is sampled using a zero crossing sampler. To extract phase and frequency information from $\{x(i)\}$, two other sequences $y(i)$ and $z(i)$ are required. The zero crossing interval sequence $\{y(i)\}$ is defined as

$$y(i) = x(i+1) - x(i) \quad i = 1,2,\ldots,N-1 \tag{2}$$

$y(i)$ is $1/2f_i$, where f_i is the instantaneous frequency. The zero crossing interval difference sequence $\{z(i)\}$ is defined as

$$z(i) = y(i+1) - y(i) \quad i = 1,2,\ldots,N-2 \tag{3}$$

$z(i)$ is a measure of the variation in $y(i)$.

It is stated that intersymbol transition (IST) affects the accuracy in estimating the carrier frequency and symbol rate. Theoretically, IST from one symbol to the next occurs instantaneously. By ignoring these IST samples, the sequences $\{y(i)\}$ and $\{z(i)\}$become $\{y_a(i)\}$ and $\{z_a(i)\}$respectively. N_y is the length of the resultant $\{y_a(i)\}$sequence.

2.1 PDF of Zero-Crossing Related Variables

The received waveform $r(t)$ consists of a sinusoid plus noise [5]:

$$r(t) = A\cos 2\pi f_c t + \upsilon(t) \quad 0 \le t \le T_o \tag{4}$$

where A and f_c are the amplitude and frequency of the sinusoidal wave respectively. The ith zero-crossing point can be written as:

$$x(i) = \frac{i = 0.5}{2f_c} + \alpha(i) \quad i = 1,2,\ldots,N \tag{5}$$

where $\alpha(i)$ are i.i.d. random variables that represent the variation due to $\upsilon(t)$. An asymptotic expression of the pdf of $\alpha(i)$ is shown to be a Gaussian form with zero mean and variance

$$\sigma_\alpha^2 = \frac{1}{2(2\pi f_c)^2 \gamma} \tag{6}$$

where γ is the CNR and is defined as $\gamma = A^2/2\varphi(0)$. The zero crossing interval $y(i)$ is given by:

$$y(i) = \frac{1}{2f_c} + \varepsilon(i) \tag{7}$$

where the interval variation $\varepsilon(i) = \alpha(i+1) - \alpha(i)$.
It is shown in [5] that the pdf of the interval variation can be approximated by the Gaussian density function with zero mean and variance

$$\sigma_\varepsilon^2 = \frac{1}{(2\pi f_c)^2 \gamma}\left[1 + \rho\left(\frac{1}{2f_c}\right)\right] \tag{8}$$

where $\rho(\tau) = \varphi(\tau)/\varphi(0)$ is the normalised autocorrelation function. It follows that the pdf of $y(i)$ is:

$$f(y) : N(1/2f_c, \sigma_\varepsilon) \tag{9}$$

3 CLASSIFICATION PROCEDURE

The procedure for digital signal classification is based on the method outlined in [3]. The intercepted signal with length K seconds and sampled at sampling rate f_s is divided into M successive frames. Each frame is N_s samples long (N_s = 2048) which is equivalent to 1.76ms. This results in M $(=Kf_s/N)$ frames. A set of key features is extracted from each frame to decide the type of modulation.

3.1 Key Feature Extraction

The zero crossing interval sequence $\{y_a(i)\}$ is reported to be a staircase type signal in [Hsue and Soliman, 1989] where the stair levels correspond to the signal states. In our simulation the bandlimiting of the FSK signals makes the differentiation of the signal states very difficult. Therefore a method using the number of peaks in the histogram of $\{y_a(i)\}$and the value of the first bin in the histogram of $\{y_a(i)\}$is used.

By observing the histogram of $\{y_a(i)\}$ for FSK4 and FSK8, it is found that the first peak in the histogram is slightly higher for FSK8 than for FSK4 and its value is around 500. Also by observation of 400 realisations from each modulation type, it is found that for SNR of 20dB and 15db, the number of peaks in the histogram for FSK4 is 4 and 5. For the SNR of 10dB, the number of peaks is 5 and 6. It is also determined that the number of peaks in the histogram for FSK8 is ≥ 4.
Therefore two key features are used:

- The first is P_{zero} which is the number of peaks in the histogram of $y_a(i)$.
- The second is P_{max} which is the number of occurrences in the first bin of the histogram of $y_a(i)$.

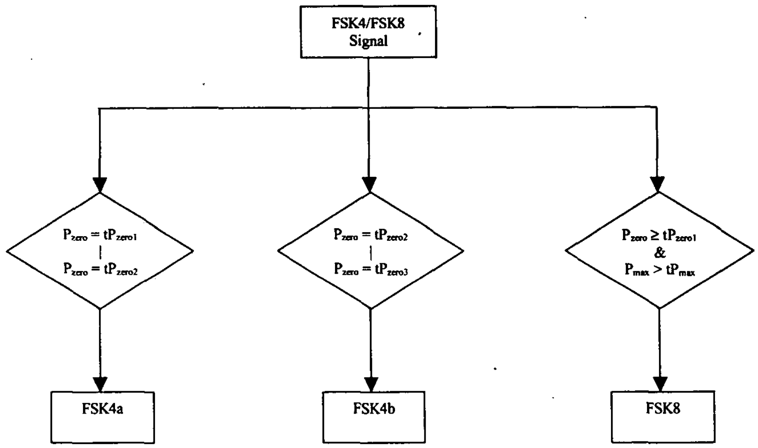

Figure 1. Flowchart for identification of FSK4 and FSK8 Signals

4 DECISION-THEORETIC APPROACH

A flowchart depicting the classification procedure is shown in Figure 1. Three simultaneous decisions are made by comparing a key feature value of the signal with a certain threshold. The decision with the highest incidence is chosen as the correct signal. The thresholds are chosen so that the number of correct decisions made is optimal.

The threshold values for the DT approach were found by referring to the histogram of of $\{y_a(i)\}$ for FSK4 and FSK8 and by observing the number of peaks in the histogram for 400 realisations of each modulation type at SNR of 20dB, 15dB and 10dB. The relevant thresholds and their corresponding values are $tP_{zero1} = 4$, $tP_{zero2} = 5$, $tP_{zero3} = 6$ and $tP_{max} = 490$.

5 NEURAL NETWORK CLASSIFIER

The two key features: P_{zero} and P_{max} are normalised to the range −1 to 1 and passed to the neural network structure. The NN classifier is a feedforward network which has two input nodes corresponding to the two key features and two output neurons corresponding to the FSK4 and FSK8 signals.

Three network structures are analysed at different SNR to determine the optimum structure. The first network has two hidden layers with each layer having two neurons. The success rate is 100% but the structure may be too big for the task. The second structure has one hidden layer with four neurons. This also gives 100% success rate but may also be too complex for the task. The third structure has one hidden layer with two neurons and is chosen as the optimum structure because it gives 100% classification success rate and is the simplest design.

In general it is found that the smaller structures are the optimum choice for the following reasons [7]:

- The small structures are the least complex and therefore are the fastest to train since they contain the least number of synapses.
- Smaller structures also minimize the danger of overfitting and loss of generalization ability since they have the least "memory".
- The larger networks have lower success rate due to their poorer generalization ability.

In all cases the hidden layers use the nonlinear tan-sigmoid (hyperbolic tangent) activation function because it enables better feature extraction and normally results in a smaller network. It also generally allows the network to learn faster [8]. The output layer is a log-sigmoid function since the ideal output should be 1 (true) and 0 (false) for all other outputs. The block diagram of the neural network classifier is shown in Figure 2.

5.1 Training the Network

All networks are trained using the Levenberg-Marquardt (LM) algorithm. This algorithm is currently one of the fastest training algorithms and approaches second-order training speeds.

Two hundred samples from each modulation type are used to train each tested network. Each network is also tested and validated using a separate set of 200 samples of each modulation type. While training, a mean square error performance goal is given and a cross validation set is used to stop the training early if overfitting occurs to maintain a good generalisation performance [8]. The target values for true and false are offset from 1 and 0 (limit values for log-sigmoid function) to 0.9 and 0.2 respectively to improve the speed of convergence [8]. The fast convergence properties of the LM algorithm in addition to offsetting the limit values, allows the network to be trained for a maximum of only 3000 epochs. It is found in [7], that training the network with a mix of samples with SNR 20dB and 10dB gives the best overall performance over a good spread of SNR.

6 PERFORMANCE RESULTS

The performance results were derived from 400 realisations of each modulation type. The carrier frequency, sampling rate and the symbol rate were given values of 150kHz, 1200kHz and 12.5kHz respectively. The digital symbol sequence was randomly generated. Signals are bandlimited according to the technique outlined in [3] where the bandwidth B_w contains 97.5% of the total average power. The MFSK bandwidth is found to be $8R_s$ where R_s is the symbol rate.

A comparison is made between the overall results from the decision theoretic (DT) approach and the NN approach. It can be seen from Table 1 that the NN classifier is clearly superior over the DT classifier with 100% success rate even at the SNR of 5dB.

SNR	20dB	15dB	10dB	5dB
Neural Network	100%	100%	100%	100%
Decision Theoretic	98.88%	98.12%	98.5%	52.25%

Table 1: Comparison of performance between the NN-based and DT-based classifiers.

Once the key features have been identified, the NN is able to learn the classifications directly from the training data. In contrast to the DT approach, there is no need to determine a classification algorithm or threshold values. The NN approach also performs exceptionally well for SNR of 5dB though the network is trained for SNR of 20dB and 10dB, while the DT approach performs badly at SNR of 5dB. The threshold values are chosen based on data at SNR of 20dB and 10dB and this explains the drop in performance at SNR of 5dB.

7 CONCLUSIONS

The paper has proposed two algorithms to distinguish between bandlimited FSK4 and FSK8 signals. The first algorithm is a decision-theoretic approach and the second algorithm is a neural network implementation. Key features are extracted from the signals of interest using zero-crossing techniques. The optimum thresholds are found for the DT approach a novel decision tree is proposed. For the neural network, the optimum structure was found to have two input nodes, one hidden layer with two neurons and two output neurons. The performance results were compared for both techniques and it was found that the NN outperformed the DT approach considerably, especially at SNR of 5dB. The NN consistently gave 100% success rate for all SNR. The DT performed favourably for SNR of 20dB, 15dB and 10dB with success rates > 98% but at the SNR of 5dB, the performance dropped dramatically to 52.25%. This is due to the fact that the threshold values are chosen based on data at SNR of 20dB and 10dB.

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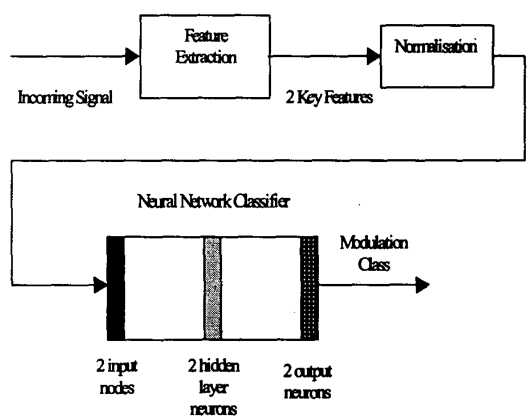

Figure 2: Block Diagram of Neural Network-based Modulation Classifier