AUTOMATIC CLASSIFICATION OF QAM SIGNALS BY NEURAL NETWORKS

Shintaro Taira

Technical Research and Development Institute, Japan Defense Agency

1-2-24 Ikejiri Setagaya-ku Tokyo 154-8511 Japan

ABSTRACT

In this paper, automatic classification of QAM signals including 64-state QAM and 256-state QAM is discussed. Three layer neural networks whose input data is the histogram distribution of instantaneous amplitude at symbol points is used for the classification. The evaluations of classification performance are carried out for both cases in which the synchronization of symbol timing is assured at the receiver and not assured. Good classification results are obtained by the computer simulations at SNR 10dB. The influence of the number of symbol points which are used for the calculation of histogram is also discussed.

1. INTRODUCTION

Automatic modulation classifier can be defined as the system which identifies the modulation type of input signal automatically and reports the estimation results, and has many applications in the field of communication. For example, this technique can be applied to the universal demodulator which can recognize the opposite modulation types in real time and choose the optimum demodulator.

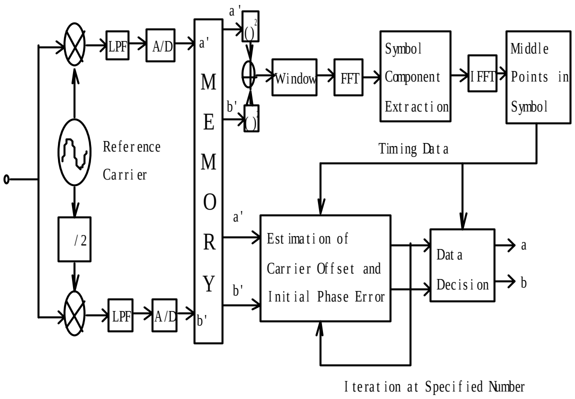
Many investigations about automatic classification of modulation signals have been carried out in the past. As for the classification of digital modulation signals, there are following investigations. Soliman et al developed the classification algorithm based on the nth moment of signal phase to classify M-ary PSK signals [1,2]. Nandi et al classified some digital modulation signals by the spectrum symmetry around carrier frequency, standard deviation of instantaneous amplitude and so forth [3].

Those abovementioned investigations did not discuss the classification of QAM signals, because QAM has not been generally used in the past. However, with the recent advance of communication technologies, QAM has become used especially for high capacity radio communication. Therefore, interest for QAM signal classification is increasing, and some investigations have been carried out recently. Sills proposed the maximum-likelihood algorithm which is based on the probability density function of amplitude and phase difference [4]. Yang et al proposed the log-likelihood function-based algorithm for QAM classification based on the probability density function of amplitude and classified 16QAM and 32QAM signals[5]. However, the classification method based on the maximum-likelihood algorithm is difficult to be applied to QAM signals whose constellations are square and mutually close[6]. Therefore, it is desirable that the pattern recognition method such as neural networks with generalization ability which enables to recognize unknown patterns is applied to the classification of QAM signals. In this study, neural networks whose input expresses the distribution of instantaneous amplitude at symbol points is applied to the classification of QAM signals including 64-state QAM and 256-state QAM. And we also evaluate the case in which the synchronization of symbol timing is unknown at the receiver (asynchronous case). For the estimation of symbol timing, the block demodulation method based on the block processing of input signal [7] is used in this study.

This paper is organized as follows. In Section 2, the block demodulation method and its estimation performance of symbol timing are shown. The structure and learning algorithm of neural networks are explained in Section 3. The evaluation results of classification performance are discussed in Section 4, and conclusions are presented in Section 5.

2. BLOCK DEMODULATION

In this section, block demodulation method to estimate the symbol timings of input signal by block processing is explained. Fig.1 shows a block diagram of block demodulator. Block demodulator consists of three parts as follows, the quasi synchronous orthogonal demodulator, the estimator of symbol timing based on



Fi g.1. Block demodulator.

FFT processing and the estimator of carrier information based on the least square method. In this study, exact estimation of carrier information is not necessary. Therefore, the explanation of estimator of carrier information is omitted.

In the quasi synchronous orthogonal demodulator, received signal is multiplied by a fixed reference carrier which is adjusted around the true carrier frequency. Therefore, quasi in-phase(I) and quadrature-phase(Q) components obtained by the demodulator have the carrier frequency offset and initial phase error. Those components can be given by

where $a(t)$ and $b(t)$ are true I and Q components, Δf is the carrier frequency

$$a'(t) = a(t)\cos(2\pi\Delta f t + \theta_0) + b(t)\sin(2\pi\Delta f t + \theta_0), \quad (1)$$

$$b'(t) = b(t)\cos(2\pi\Delta f t + \theta_0) - a(t)\sin(2\pi\Delta f t + \theta_0), \quad (2)$$

offset, and θ_0 is the initial phase error. The influence of carrier frequency and initial phase error can be eliminated by the calculation of square sum of I component and Q component. The square sum component can be expressed as

$$a'^2(nT_s) + b'^2(nT_s) = a^2(nT_s) + b^2(nT_s), \quad (3)$$

where T_s is the sampling period of AD conversion. These square sum components can be regarded as the symbol rate components. Therefore, symbol rate components can be obtained by FFT processing of these square sum data and choice of maximum peak component. However, symbol timing is generally asynchronous to the sampling timing, and maximum peak component is not an exact symbol rate component. Therefore, maximum peak component and largest one among the adjacent components are chosen as the symbol rate components and processed by inverse-FFT.

Real components and imaginary components obtained by inverse-FFT are the phase components of symbol rate which is given by

$$\mathrm{Re}\,al = \cos(2\pi f_b nT_s + \theta), \quad (4)$$

where f_b is the symbol rate frequency. Symbol rate phase can be obtained by arctangent between the real component and imaginary component and expressed as

Symbol points are defined as the middle points of each symbols where

$$\mathrm{Im}\,ag = \sin(2\pi f_b nT_s + \theta), \quad (5)$$

$\phi(nT_s)$ equals to π. However, symbol points should be decided by interpolation in this case because symbol timing is asynchronous to sampling timing. We used the spline curve method for interpolation.

$$\phi(nT_s) = [2\pi f_b nT_s + \theta] \bmod 2\pi. \quad (6)$$

Fig.2 shows the estimation result of symbol rate obtained by block demodulation method. The conditions for computer simulations are as follows.

3.7 carriers per symbol period
4.7 sampling points per carrier period
initial phase error to true carrier : 0.1rad
cosine roll-off factor of band-limitation filter : 1.0
8192 sampling points per analysis block

Modulating signals are generated by FSR sequences which is given by

In this study, constellation configurations of QAM signals are supposed to

$$1 + x^4 + x^{53} = 0. \quad (7)$$

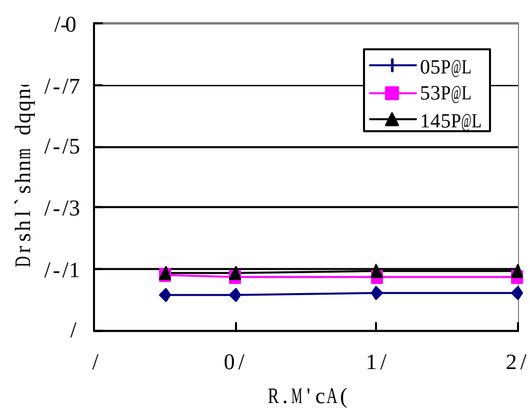
be square type.

In the figure, estimation error is expressed as the relative error to the true value. 100 simulations are carried out for each modulation type and SNR, and averages are shown in the figure. It can be known that estimation errors are below 0.02% for all cases and symbol rate can be estimated precisely.

Fig.2. Estimation result of symbol rate.

3. NEURAL NETWORK MODEL

We have used three layer neural networks with a hidden association layer for the classification of QAM signals. The input to networks is the histogram



distribution of instantaneous amplitude at symbol points. The division number of histogram, which equals to the number of units in the input layer, is chosen to be 50 for minimizing the correlations between QAM signals.

The input-output function of input layer units is the linear function, and the ones of association layer units and output layer units are the log-sigmoid function. Back propagation learning method is used for training networks. We have chosen the learning rate and stabilized constant which decide the learning speed to be 0.1 and 0.9 respectively.

Furthermore, we have applied some methods to optimize the network structure. Generally, the optimum number of association layer units is unknown and decided empirically. In this study, we have used goodness factor G_i^k [8] to decide the optimum number of association layer units. Goodness factor is defined as

$$G_i^k = \sum_p \sum_j \left(w_{i,j}^{k,k+1} O_i^k(p) \right)^2 , \qquad (8)$$

where p is the pattern of input data, w is the weight function and O is the output of unit. Goodness factor expresses the total output which propagates into the forward direction in the learning process. Therefore, an unit with minimum value of goodness factor can be regarded as most useless unit from the viewpoint of recognition and removed from networks. And there is also a problem that neural networks fall into the local minimum and cannot escape from there. We have used Network excitation method [9] to prevent networks from falling into the local minimum. This method maintains the output of each unit between 0.1 and 0.9, therefore the networks can be activated continually.

Fig.3 shows the iterative learning algorithm. If learning is practiced in the predetermined times and the recognition is successful for all learning data, most useless unit detected by goodness factor is removed and networks is initialized by Network excitation method. If recognition failed and iterative number of learning is above the predetermined threshold value, an unit is added to the association layer and learning continues.

The histogram of 16QAM, 64QAM and 256QAM signals at SNR=30,20 and 10dB are used for the learning. Two cases when symbol timing is ensured (synchronous case) or estimated by block demodulation method (asynchronous case) are learned. Namely, 18 learning data sets are used. Numbers of symbol

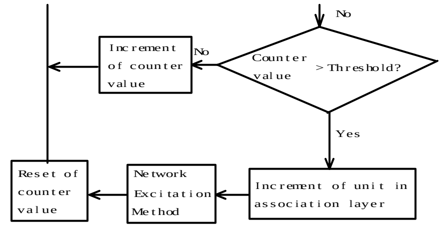
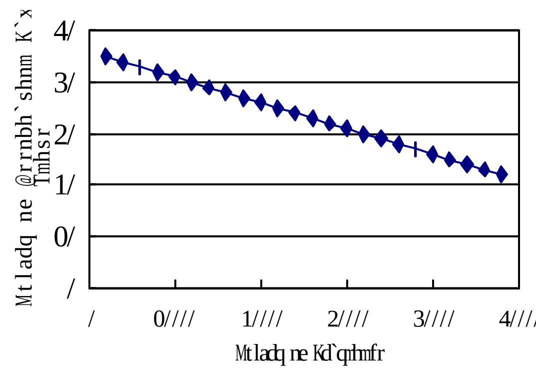


Fig.3. Iterative learning algorithm.

Fig.4. Number of association layer units.

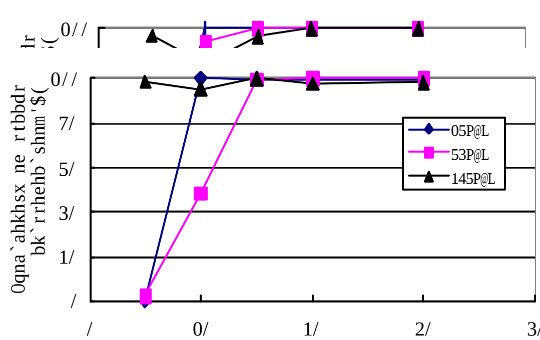


points used for the calculation of histograms are 2000 for synchronous case and 471 for asynchronous case respectively.

Fig.4 shows the change of number of association layer units in the learning process. It can be known that the number of units is decreased continuously by the removal of useless units. We have chosen the number of units to be 34 in consideration of the error between teaching signal and actual network output.

4 PERFORMANCE EVALUATION

Fig.5 and 6 show the results of performance evaluation of neural networks. 500 trials are practiced for each modulation types and SNR, and 400 symbol points are used for the calculation of histogram. If all outputs of output layer units do not exceed 0.5, input signal is regarded as unknown modulation type. As for the synchronous case, good classification results are obtained



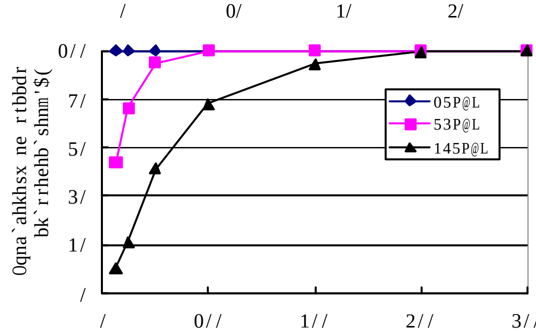


Fig.7. Change by number of symbol points (synchronous case).

for all modulation types at SNR 10dB. However, as for the asynchronous case, classification performance for 64 QAM begins to be worse at SNR 15dB. Good classification performance is obtained for 256QAM even at low SNR. It is because distribution of instantaneous amplitude becomes uniform at low SNR and all QAM signals tend to be classified as 256QAM.

Fig.7 shows the change of successful classification rate by the number of symbol points used for the calculation of histogram. It

can be known that 256QAM signal is most influenced and the classification rate begins to fall at number=200. Threshold number of symbol points for 64QAM is about 50, and as for 16QAM, good classification performance is obtained even at number=13.

5. CONCLUSIONS

We have evaluated the classification performance of three layer neural networks for QAM signals. Threshold SNR for correct classification are about 10dB for synchronous case and 15dB for asynchronous case respectively. All QAM signals tend to be classified as 256QAM signal at low SNR because distribution of instantaneous amplitude becomes uniform. Threshold number of symbol points for the correct classification of each modulation signal is also obtained.

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