MODULATION CLASSIFICATION – AN UNIFIED VIEW

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ABSTRACT

There are many research papers published in modulation classification, and most of them have a common framework. In this paper we will give an overview, and the paper contains four topics: 1) Some fundamental principles, 2) features used for classification, 3) the algorithm structure, and finally 4) a literature survey.

1 INTRODUCTION

In electronic warfare (EW), electronic support (ES) plays an important rôle as a source of information required to conduct electronic attack (EA), electronic protection (EP), and threat detection/recognition.

Traditionally, the surveillance of the electromagnetic environment is performed manually by human operators. However due to the increasing activity in the frequency spectrum automated techniques are becoming desirable. The task of signal interception consists of detection and classification. The classification can be accomplished by comparing the characteristics of the intercepted signals against a catalogue of characteristics or sorting parameters. One important sorting parameters is the *modulation type*.

There are several papers published in the area of modulation classification (MC), and many of them have a common framework. In this contribution, we will give an overview focusing on general principles extracted out from the studied literature. The main topics for this paper will be: 1) Some fundamentals focusing on basic principles for modulation, MC, and the transportation process, 2) features typically used for MC, 3) the generic modulation classifier and 4) a literature survey.

2 SOME FUNDAMENTALS

2.1 Modulation

In radio communication the message signal is transported by the carrier signal $e^{i\omega_c t}$, where ω_c is the carrier frequency. Through the modulation $\mathcal{M}$, the message signal $m(t)$ is attached to the carrier signal through the complex envelope $z(t)$, i.e., we have the mapping $m(t) \xrightarrow{\mathcal{M}} z(t)$. We thus get the radio signal

$$\begin{aligned} r(t) &= \Re\left[z(t)e^{i\,\omega_c t}\right] && (1) \\ &= x(t)\cos\omega_c t - i\,y(t)\sin\omega_c t, && (2) \end{aligned}$$

where $z(t) = x(t) + i\,y(t)$, $x(t)$ is the in–phase component, and $y(t)$ is the quadrature–phase component.

2.2 Modulation Classification

We know the complex envelope $z(t)$, the result of the mapping $m(t) \xrightarrow{\mathcal{M}} z(t)$, and want to deduce the modulation type $\mathcal{M}$ and/or the message signal $m(t)$ from it. The far most common problem treated in the literature is to estimate the modulation type only.

To derive the modulation type $\mathcal{M}$ we must extract features from $z(t)$. Since our primary interest is in the modulation type $\mathcal{M}$, we must *enhance* the influence of the modulation type and *suppress* the influence from the message signal $m(t)$. To suppress the influence of the message signal $m(t)$ it is convenient to study some type of *distribution* that do not contain time information. Commonly one uses parameters describing the distribution instead (mean, variance, skewness, and kurtosis) to reduce the information to be processed by the classifier.

Sometimes a mathematical de
bution is available. One can then use hypothesis testing to decide among given modulation types.

Let us rephrase the above discussion like follows. By studding the mapping $m(t) \xrightarrow{\mathcal{M}} z(t)$ we want to be able to determine the modulation type of the signal. This problem can be more easily solved by studying the mapping

$$f(\mathcal{D}_x m(t)) \xrightarrow{\mathcal{M}} f(\mathcal{D}_y z(t)), \tag{3}$$

where $\mathcal{D}_x$, $\mathcal{D}_y$ denotes the distribution of some parameter derived from its argument (the signals $m(t)$ and $z(t)$ respectively) and f is some processing which is done with the distribution. Often we do not have to know the actually value of the message signal $m(t)$ to compute $f(\mathcal{D}_x m(t))$, we only need to know some properties of the message signal.

2.3 The Transportation Process

In the transportation process, where the message signal is carried over from the transmitter to the receiver, the signal will be disturbed. Two components are here of interest, the channel and the receiving system. The disturbances will make the MC process harder and must therefore be compensated for by the pre–processor.

2.3.1 The Channel

During the transportation of the radio signal in the channel it will be distorded. The signal will be affected by fading $\mathcal{F}(t,\omega)$, noise $n(t)$, large amplitude peaks (outliers) $o(t)$, and interfering signals $i(t)$. We now get

$$\tilde{r}(t) = \mathcal{F}(t,\omega)r(t) + n(t) + o(t) + i(t), \tag{4}$$

where $\tilde{r}(t)$ is the distorted signal.

2.3.2 The Receiver

The receiver and the receiving antenna will add their noise to the signal. Here we let it be part of the channel noise $n(t)$ described above. The receiver will down–convert[1] and IQ–decompose[2] the signal and we get

$$\begin{aligned} \hat{z}(t) &= \left(\tilde{r}(t) + i\,\hat{\tilde{r}}(t)\right) e^{-i(\omega_c - \Delta\omega)t} && (5) \\ &= \mathcal{F}(t,\omega) z(t) e^{i\Delta\omega t} + n(t) + o(t) + i(t). && (6) \end{aligned}$$

In the expression above we use the same notation for noise etc. in the channel and after down conversion and IQ–decomposition to simplify the presentation. The receiver will introduce a frequency offset $\Delta\omega$ due to inaccurate knowledge of the true center frequency. The obtained version of the complex envelope $\hat{z}(t)$, that can be processed to determine the modulation type, is disturbed by the channel and by the receiver as described in this presentation. To be able to do reliable MC, we need to clean up the signal first.

3 THE FEATURES

There is a large variation in the literature about the features used for MC. Basically there are only variations on the same theme. The features can be divided into two main groups: time–domain and frequency– domain features. We will describe these main groups here.

3.1 Time–domain features

Time–domain features are obtained from the expression of the complex envelope

$$z(t) = R(t)e^{i(\int_0^t \omega_i(s)ds + \phi(t))}, \tag{7}$$

where $R(t)$ is the amplitude, $\omega_i(t)$ is the instantaneous frequency, and $\phi(t)$ is the phase of the complex envelope respectively. These three quantities and combinations of them together wit

the time domain features. The measured radio signal is provided as in–phase and qudarture–phase components $z(t) = I(t) + i\,Q(t)$, and the time–domain parameters are computed as follows:

[1] The signal is moved to a lower intermediate frequency (IF).

[2] The IQ–decomposition converts the "real" radio signal into a complex version.

Amplitude $R(t) = \sqrt{I^2(t) + Q^2(t)}$

Phase $\phi(t) = \arctan \frac{Q(t)}{I(t)}$

Differential Phase $\Delta\phi(t) = \phi(t) - \phi(t-T),\ T =$ symboltime

Instantaneous frequency $\omega_i(t) = \frac{d\phi(t)}{dt} = \Im\left(\frac{dz(t)/dt}{z(t)}\right)$

Zero crossing time sequence

$$\begin{aligned} t_{z,k} &= \{t, I(t) = 0\} && (8) \\ T_{z,k} &= t_{z,k} - t_{z,k-1} && (9) \\ \omega_{i,k} &= \frac{\pi}{T_{z,k}} && (10) \end{aligned}$$

3.2 Frequency– domain features

In the frequency– domain we basically analyze the power spectrum (energy distribution as a function of frequency). Dependent on the characteristics of the signals one can use:

Stationary spectrum: Estimating the power distribution direct from the FFT gives a very erratic function. To reduce the variance of the spectrum some averaging is needed as in Welch method.

Cyclostationary spectrum: Radio signals and most man–made signals have the characteristics of being cyclostationary, i.e., the covariance and the spectrum varies periodically with time.

Non–stationary spectrum: There exist MC methods that have been using non–stationary spectral estimates as features. Several such estimates exist like the *Wigner–Ville distribution* [7], *wavelets* [7], and many other methods.

Higher order moment spectrum: A small number of modulation classifier have been based on higher order spectrums, see [14].

3.3 Feature processing

The features are often some distribution (pdf – probability density function) or some parameters describing the distribution. The distribution describing parameters computed are, among others, the following: *Mean)* $\bar{x} = \mathrm{E}x$, *Variance)* $\sigma^2 = \mathrm{E}(x-\bar{x})^2$, *Skewness)* $\gamma_1 = \frac{\mathrm{E}(x-\bar{x})^3}{\sigma^3}$, *Kurtosis)* $\gamma_2 = \frac{\mathrm{E}(x-\bar{x})^4}{\sigma^4}$.

4 THE GENERIC MC

Here the "generic" modulation classifier (MC) is outlined. First, the basic building blocks in the MC algorithm are presented. These building blocks can be implemented differently dependent on the features to be used and the modulation types the MC must be able to classify. In the block diagram in figure 1, we see the different data processing blocks. We have:

Receiver Processing

Processes the analogue radio signal so it will be prepared for further processing. This step typically includes down conversion, quadrature–decomposition, and sampling.

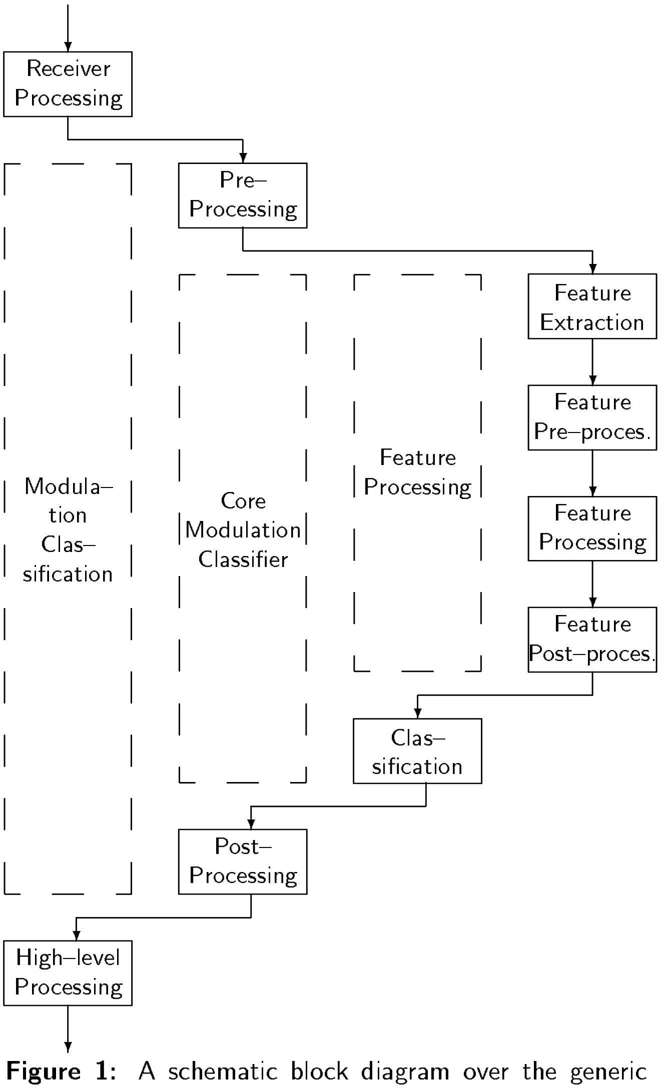

Figure 1: A schematic block diagram over the generic modulation classification algorithm.

Modulation Classification

The MC computes some significant features from the received radio signal, and determines the modulation type outgoing from these features. This is done as follows.

Modulation Classification – Pre–processing

A crucial component for implementing a successful MC is the pre–processor. It has to process the intercepted signal so it will be in line with the assumptions on which the MC was designed. The MC will process the complex envelope $z(t) = \mathcal{M}m(t)$ and the disturbances described in Section 2.3 must be compensated for. We have:

Remove amplitude peaks (outliers): Impulsive disturbances, whit short and large amplitude peaks that will severally disturb the MC.

Remove noise segments: In modulation forms that do not have carrier components, pauses in the message signal will generate noise segments, which will confuse the MC.

Remove carrier segments: If the modulation type generates carrier components, pauses in the message signal will generate carrier segments. These segments have little information about the modulation type and should be removed.

Removing interfering signals: Problems for the MC are also given by strong signals close to the signal of interest. Here one has to localize where the signals are and extract interesting components.

Increase the SNR of the signal: Most of the developed MCs need reasonable good SNRs to operate properly. One method to increase the SNR is to adjust the bandwidth of the signal so it corresponds to the modulated signal.

Compensate for fading: Fading introduces an unwanted amplitude modulation, and will distort the amplitude information. The modulation induced amplitude variation is faster than the fading induced. This makes it possible to estimate the slowly varying fading envelope and compensate for it.

Compensate for carrier offsets: Often the true carrier frequency for the signal of interest is unknown. This will result in a frequency offset that will distort the phase information.

Modulation Classifier – Core Classifier

The core MC basically does the work of a pattern matcher. A decision theoretic approach can also be used, and is based on known pdfs and hypothesis testing. The core classifier contains two main blocks, the feature processor and the classifier.

MC – Core Classifier – Feature Processing

The features to be used for MC must be selected so they are sensitive to the modulation types of interest. Then the features must be processed to enhance modulation dependence and to suppress message dependence. The feature processing carried out are the following tasks:

Feature extraction: The features to use are extracted from the signal.

Feature pre–processing: Often the extracted feature must be pre–processed to remove disturbances.

Feature processing: The features are processed to obtain characteristics that can be used to discriminate between different modulation types. Often some type of distribution is estimated or distribution describing parameters as mean, variance, skewness, and kurtosis. One can also compute some test statistics that can be used in hypothesis testing.

Feature post–processing: The features are post–processed to enhance significant features and suppressing insignificant features. Often the feature set contains redundancy, which can be reduced with the Kharunen–Löève transform or principal component analysis (PCA).

MC – Core Classifier – Classification

The classifier shall operate on extracted features and make a decision about the modulation type for the analyzed data. Several pattern matching techniques exist as linear classifier, quadratic classifier, tree–classifiers, neural–net based classifiers, hypothesis testing based classifiers and more or less *ad hoc* based classifiers.

Modulation Classifier – Post–processing

The pre–processor can split a signal containing multi tones into several single tone components, to handle interfering signals. These components will be analyzed separately. Afterwards they must be grouped together to form multi channel signals.

High Level Processing

In operational intelligence systems one often wants to carry on the classification further to include information about platforms, military units, location, direction and so on. This can be done on a higher level.

5 LITERATURE SURVEY

The published modulation classifiers (MCs) can be dissected along different cutting lines. We will here look at the features and the basic feature processing. Most of the implemented MCs are using time–domain data and only a few use frequency–domain data.

One of the first publications on MC was by Weaver and co–workers [16] and they used the frequency spectrum divided into 29 regions as a feature vector for a pattern matcher. In [6] both the smoothed spectrum and the bispectrum were used for MC. The authors found that the smoothed spectrum gave the best result. Gardner and co–workers [5] have done a lot of work with cyclostationary signals and suggested how these features can be exploited for MC.

There are many papers presenting time–domain based MCs. We have Assalleh and co–workers [2], which used instantaneous–frequency estimates derived from AR–models estimated for short data segments. Gadbois [3] suggested his own parameter (related to the kurtosis) for amplitude and some features for instantaneous frequency. These and similar parameters are also studied by the author [11].

Several histogram based MCs have been presented in the literature. Here the histogram approximates the pdf of the actual feature. Work with such MCs has been done by Liedtke [10], Jondral [9], Dominguez [4], the author [12, 13], and others. Aisbett [1] has been studying some time–domain features that are more robust against noise.

Several MCs for PSK signals have been proposed that are based on the phase pdf and hypothesis testing. Many of these MCs are working for an SNR far below 0 dB. Work here has been done by Yang and Soliman [17], Huang and Polydoros [8] and Soliman and Hsue [15].

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