RADAR PULSE CLASSIFICATION USING COMPRESSED INTRAPULSE FEATURE VECTORS

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ABSTRACT

A system for classifying/identifying single radar pulses is proposed. The classifier is based on the intrapulse features: pulse length, carrier frequency, pulse envelope and instantaneous frequency variations. The system is tested using X-band boat radars using a weighted combination of the features. In addition we apply feature compression using wavelets. This results in equal or better performance while decreasing computational complexity and storage. We obtained a probability of correct classification of 0.87 at zero probability of false classification in a test with about 2000 radar pulses containing 22 radar classes.

1. INTRODUCTION

The task of Electronic Support Measures (ESM) is to identify (fingerprint) and locate the position of emitters (radars or other radio equipment). In contrast to radar systems, ESM is passive and will only intercept signals sent by others.

Radars typically emit thousands of pulses every second and in most scenarios there are many radars operating simultaneously interleaving radar pulse trains. The process of separating each pulse train is called *deinterleaving*. Parameters commonly used and found when deinterleaving are the carrier frequency, pulse width, angle of arrival (AOA), time of arrival (TOA), and the pulse repetition interval (PRI) [1, 2]. These parameters affect the radar's performance and are useful for finding the purpose of the radar and may also help in identifying the radar.

Many radars, especially military, can change these parameters under operation (frequency agility, different PRI patterns etc.) making the deinterleaving process difficult and identification by deinterleaving very difficult. As a result one must resort to additional methods for classification and identification. The ultimate objective is to be able to identify specific radar emitters, i.e. fingerprinting of emitters.

This paper will look at a method for classifying single intercepted radar pulses based upon intrapulse features. Intrapulse features are measurements characterizing the radar pulse based on a single pulse.

This paper propose a classifier based on the intrapulse features pulse envelope and instantaneous (carrier) frequency variations. These features expose the unintentional modulation on the pulses (UMOP). UMOP are due to inherent problems in the modulation sensitivity of high-power transmit tubes [1]. Only pulsed radars with no intentional modulation or pulse compression are considered in this paper.

A set of features of known radars will typically be stored in an emitter library. Classification is done by matching features of the incoming pulse to the known radars in the emitter library. We use wavelet decomposition of the features to improve performance and reduce complexity of the classifier as well as to reduce the size of the emitter library.

The proposed classifier is tested using pulses from X-band boat radars.

2. RADAR PULSE CLASSIFICATION

Although the system is implemented digitally, most of the theory is developed using continuous-time variables unless discussing implementational issues. We denote the continuous-time radar pulse $x(t)$ and the sampled (discrete-time) version $x(n)$. The analytic extension of the pulse $x_a(t)$ defined by

$$x_a(t) = x(t) + j\frac{1}{\pi t} * x(t) \tag{1}$$

where the second part of (1) is the Hilbert transform of the signal and $*$ denote convolution [3]. The analytic signal can then be expressed as

$$x_a(t) = A(t)e^{j\varphi(t)} \tag{2}$$

where $A(t)$ is the instantaneous amplitude and $\varphi(t)$ is the instantaneous phase. This representation is useful when finding the envelope and instantaneous frequency variations.

The pulse $x(t)$ is found in a pulse detector and normalized (maximum absolute amplitude is 1) before any features are extracted.

2.1. Features

Classification of radar pulses based on matched filter directly on the pulse samples would be too sensitive to noise and time alignment as well as being too slow. As a result we would like to extract some features (signal characteristics) of the pulse that is better suited for classification purposes. The features for classifying radar pulses can be divided into *interpulse* and *intrapulse* features.

Interpulse features are derived from measurements from multiple pulses. Examples of such features are PRI, PRI pattern, pulse duration jitter and antenna scan patterns. The objective of this work is to develop a technique for classifying radars based upon one single pulse. Hence interpulse features are not available and will not be considered here.

Intrapulse features are measurements that may be found within one single pulse. The intrapulse features considered here are limited to pulse width, carrier frequency, pulse envelope and instantaneous frequency variations. This chapter introduces these features.

For other types of radar pulses additional features may be considered, such as the bandwidth, phase shifts, chirp rate or other time-frequency characteristics that are unique to the radar type.

2.1.1. Pulse width

In this paper we define the pulse width as the time difference between the start and stop points found by energy thresholding.

The average energy $E(n)$ in a window is defined by

$$E(n) = \frac{1}{N} \sum_{i=0}^{N-1} |x(n+i)|^2 \qquad (3)$$

where n is the start sample number and N the number of samples in the window. The start and stop are found by measuring when this energy exceeds and drops below a given threshold, respectively.

2.1.2. Carrier frequency

For a measurement of the carrier frequency it is common to use the average frequency of the pulse. The average frequency is defined as

$$\omega_m = \frac{1}{E_x} \int_{-\infty}^{+\infty} \omega |X(\omega)|^2 \, d\omega \qquad (4)$$

where E_x is the energy of the signal and $X(\omega)$ the Fourier transform of the pulse [4].

Practically we find the average frequency as the mean of the instantaneous frequency as described in Section 2.1.4.

2.1.3. Pulse envelope

The pulse envelope will reveal both intentional and unintentional amplitude modulation. The envelope for a given transmitter is likely to be similar from pulse to pulse. Multipath effects may alter (the tail of) the envelope, but is not considered a problem here since we assume pulses with severe multipath effects are removed before classification.

The pulse envelope is derived from (2) as the smoothed version instantaneous amplitude $A(t)$. For filtering, a simple local averaging filter is used. The envelope function $y(n)$ can then be described as

$$y(n) = \frac{1}{N} \sum_{i=0}^{N-1} A(n-i) \qquad (5)$$

where N is the filter length. (A suitable filter length is 5–10 % of the pulse length.)

To remedy poor settling time and end-effects when using (5), we use zero-phase forward and reverse filtering. That is, after filtering in the forward direction as given by (5), the filtered sequence is then reversed and run back through the filter. The filtered envelope function $y(n)$ is the time reverse of the output of the second filtering operation. The result has zero phase distortion and no settling time problems.

The envelope functions for two radar classes are shown in Figure 1(a).

2.1.4. Instantaneous frequency variations (IFV)

Due to unintentional frequency modulation at the radar transmitter the carrier frequency is seldom completely constant throughout the pulse. These deviations around the carrier frequency are often a characteristic feature of a given emitter [1, 2].

From the analytic extension of the pulse $x_a(t)$ the instantaneous phase function $\varphi(t)$ is defined by

$$\varphi(t) = \arctan \frac{\mathrm{Im}[x_a(t)]}{\mathrm{Re}[x_a(t)]} \qquad (6)$$

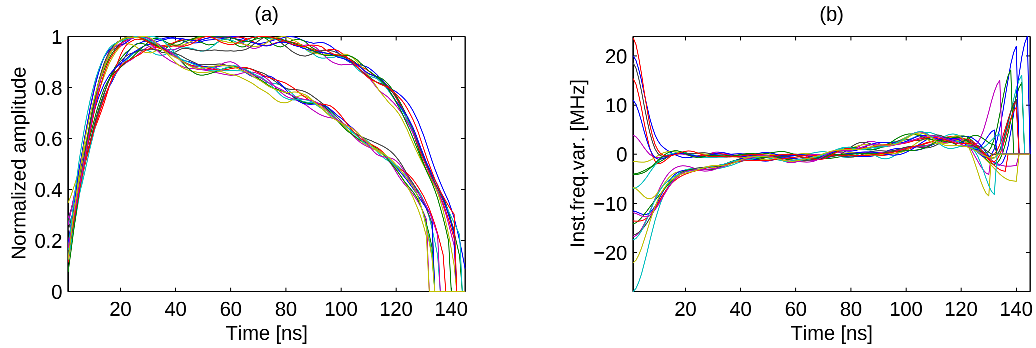

Figure 1: Feature functions for two radar classes, 10 pulses of each class. (a) Envelope function. (b) IFV function.

The instantaneous frequency $\omega(t)$ is the temporal rate of change of the instantaneous phase function:

$$\omega(t) = \frac{1}{2\pi} \frac{d\varphi(t)}{dt} \tag{7}$$

To produce a smoother instantaneous frequency function, the instantaneous phase function $\varphi(t)$ is filtered before the derivative is found. The filtering is done using a zero-phase forward and reverse FIR filter with length equal to 10 % percent of the pulse length and a normalized corner frequency of 0.01 (sample frequency is 1).

Since we want to use the deviations around the carrier frequency as a feature, the average of the instantaneous frequency function is removed. Since the filtering introduces unwanted end-effects which would affect the average frequency, the average frequency is calculated from the central portion of the pulse. This average frequency is used as the feature *carrier frequency*.

The IFV functions for two radar classes are shown in Figure 1(b).

2.2. Feature compression using wavelet decomposition

The pulse envelope function and the instantaneous frequency variation function both have the same length as the pulse itself. To reduce storage in the classifier library and to increase the computational performance of the classifier, it is desirable to reduce the size of these features. To do this we suggest wavelet decomposition. An additional effect of wavelet decomposition may be to improve the robustness of the classifier by emphasizing the characteristics of the features.

2.2.1. Wavelet decomposition

The theory of wavelet decomposition can be found in books such as [5, 6].

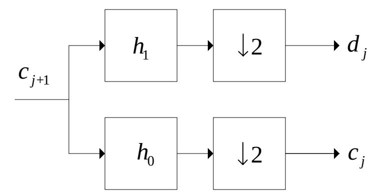

Figure 2: One level two-band analysis bank

The wavelet transform is a atomic decomposition that represents a signal $f(t)$ in terms of shifted and dilated versions of a prototype bandpass wavelet function $\psi(t)$, and shifted versions of a lowpass scaling function $\phi(t)$.

Figure 2 shows a one level analysis filter bank associated with a wavelet expansion. Associated with the filters h_0 and h_1 are the scaling function $\phi(t)$ and wavelet function $\psi(t)$ defined by

$$\phi(t) = \sum_n h_0(n)\sqrt{2}\phi(2t-n) \tag{8}$$

$$\psi(t) = \sum_n h_1(n)\sqrt{2}\phi(2t-n) \tag{9}$$

Assuming a unique solution exists, the time variable can be scaled and translated to give

$$\phi_{j,k}(t) = 2^{j/2}\phi(2^j t - k) \tag{10}$$

$$\psi_{j,k}(t) = 2^{j/2}\psi(2^j t - k) \tag{11}$$

where j is the scale.

If $\phi_{j,k}(t)$ and $\psi_{j,k}(t)$ are orthonormal or a tight frame, the j level scaling coefficients $c_j(k)$ and wavelet coefficients $d_j(k)$ of a function $f(t)$ are found by taking

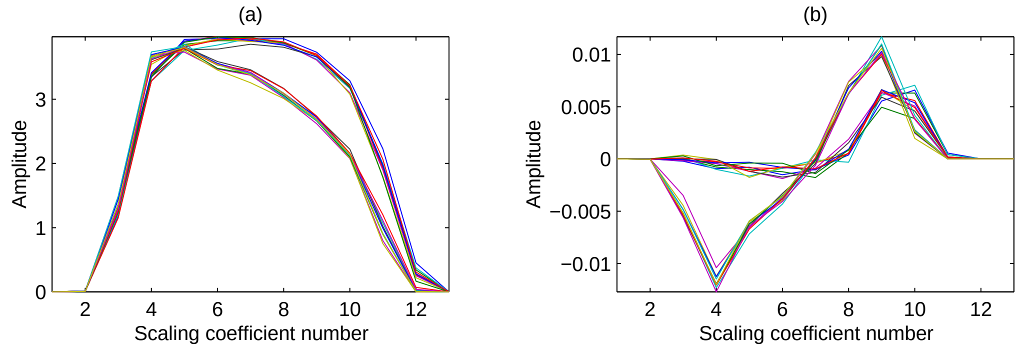

Figure 3: Compressed feature functions for same pulses as Figure 1 (a) Compressed envelope function: scaling coefficients from a 4 level decomposition using 2nd order reverse biorthogonal wavelet. (b) Compressed IFV function: scaling coefficients from a 4 level decomposition using 3rd order reverse biorthogonal wavelet.

the inner products

$$c_j(k) = \langle f(t), \phi_{j,k}(t) \rangle = \sum_m h_0(m-2k) c_{j+1}(m) \quad (12)$$

$$d_j(k) = \langle f(t), \psi_{j,k}(t) \rangle = \sum_m h_1(m-2k) c_{j+1}(m) \quad (13)$$

By iterating on the lowpass output (the h_0 branch) of the filter bank in Figure 2 a multi-stage two-band analysis tree is formed. The first stage divides the spectrum into a lowpass and highpass band. The second stage then divides the lowpass band into another (lower) lowpass band and a bandpass band and so on. By starting at a upper scale $j = J$ with the signal samples as the coefficients c_J (an approximation), a decomposition of $J - j_0$ levels (or stages) of the signal $f(t)$ can be expressed as

$$f(t) = \sum_k c_{j_0}(k)\phi_{j_0,k}(t) + \sum_k \sum_{j=j_0}^{J-1} d_j(k)\psi_{j,k}(t) \quad (14)$$

The analysis tree (iterated filter bank) calculates the discrete wavelet transform (DWT) down to as low a resolution as $j = j_0$. The coefficients c_{j_0} are the scaling coefficients of the decomposition and will describe the lowpass characteristics of $f(t)$.

2.2.2. Feature compression

As seen in Figures 1(a) and 1(b) the envelope and IFV features are of a fairly lowpass character. As a result the coefficients from the wavelet decomposition are small except for the scaling coefficients. Due to this energy concentration we suggest a feature compression by only keeping the scaling coefficients for each feature.

Although the wavelet transform is not shift-invariant, this is not considered a problem here since the signals used (envelope and IFV) are of a lowpass character and is already aligned in the pulse detector.

The end effects from calculating the IFV (see Figure 1(b)), is removed prior to feature compression (wavelet decomposition). This will make the IFV feature more similar from pulse to pulse within a class. The compressed envelope and IFV functions for two radar classes are shown in figures 3(a) and 3(b), respectively. Notice the tight clustering of the pulse features for each radar class.

2.3. Classifier

The radar pulse classification is done using a two-stage classifier. The first stage uses two single-value features, *pulse width* and *carrier frequency*, and is used for narrowing down the number of potential classes. This is done by selecting a subset of classes from the emitter library with pulse width and carrier frequency within a given range of the values measured from the unknown pulse. By ruling out certain classes by simple parameters we improve the performance of the classifier.

The second stage of the classifier works on the subset of classes found from the first stage. Here the DWT scaling coefficients of the *envelope* and *IFV function* of the unknown pulse are correlated with coefficients of the classes in the subset. The cross-correlation coefficient at zero lag is calculated for both envelope and IFV scaling coefficients:

$$\rho_{e,i} = \frac{\sum_k v_m(k) v_i(k)}{\sqrt{\sum_k v_m^2(k) \sum_k v_i^2(k)}} \quad (15)$$

$$\rho_{f,i} = \frac{\sum_k f_m(k) f_i(k)}{\sqrt{\sum_k f_m^2(k) \sum_k f_i^2(k)}} \quad (16)$$

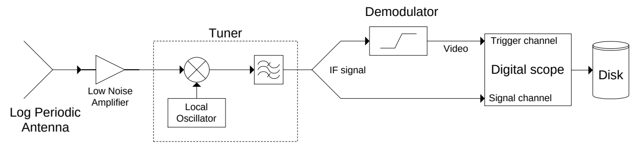

Figure 4: System for intercepting pulses used for this paper

for all classes i in the subset from the first stage. (This is a simplified matched filter since we only calculates the zero lag.) $\rho_{e,i}$ and $\rho_{f,i}$ are the cross-correlation coefficient at zero lag between the unknown pulse and radar class i for the envelope and IFV function, respectively. $v_m(k)$ and $v_i(k)$ are the compressed envelope functions of the measured (unknown) pulse m and radar class i, respectively. $f_m(k)$ and $f_i(k)$ are the compressed IFV functions of the measured (unknown) pulse m and radar class i, respectively. The class i with the maximum correlation is chosen by

$$i = \arg \max_{j \in \{subset\}} (w_1 \rho_{e,j} + w_2 \rho_{f,j}) \tag{17}$$

where w_1 and w_2 are the weights of the two features. No class is chosen (pulse rejected) if

$$\max_{j \in \{subset\}} (w_1 \rho_{e,j} + w_2 \rho_{f,j}) < \beta \tag{18}$$

where β is the reject threshold.

3. RESULTS AND DISCUSSION

In this section we test our classifier on radar pulses from various X-band boat radars.

The pulses used for this paper were collected using a system similar to the block diagram in Figure 4. We used a total of 3937 pulses divided into 22 different classes. The pulses available were unevenly distributed among the classes. Still the classification system assumes equal a priori class probabilities (unbiased classifier). The mean pulse width of the classes varied from 0.06 μs to 0.9 μs. The SNR for the pulses varied from 10 dB to 41.5 dB. Half of the pulses were used as the "training" set, the other half were used as the test set. By "training" we mean averaging the features for each class to develop an emitter library.

We use ROC (Receiver Operating Characteristics) curves to present our results. The ROC curves show the probability of correct classification as a function of the probability of false classification. ROC curves are obtained by varying the reject threshold β.

Since we primarily want to test the envelope and IFV features we allow most of the classes to pass the

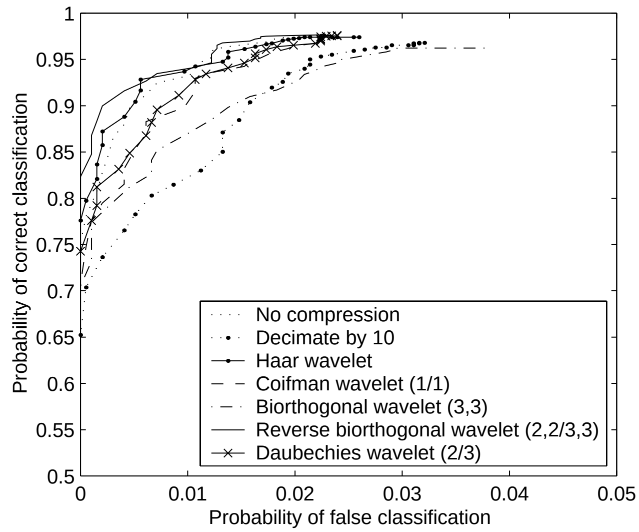

Figure 5: ROC curve for classification using different types of feature compression/wavelets. Feature weighting is 0.5/0.5 (env/IFV). 4 levels of wavelet decomposition. Order of wavelet in parenthesis (env/ifv).

first stage of the classifier by setting wide range of pulse widths and carrier frequencies.

Figure 5 shows the result of the classification for different types of feature compression, including no compression at all. When wavelet compression are indicated, 4 levels of wavelet decomposition were used. The features were weighted equally. From these results we see that the reverse biorthogonal wavelet [6, pages 273–275] performs best, even better than for no compression at all. The Haar wavelet performs about the same as when no compression is applied. We note that simply lowpass filtering and decimating the features gives worse results than wavelet decomposition. Wavelet decomposition generally seems to give better compression for the same performance curve than simply lowpass filtering and decimating.

We will continue our tests using the 2nd and 3rd order reverse biorthogonal wavelets for the envelope and IFV features, respectively, since these wavelets provided good results.

Figure 6 shows the result of the classification for different feature weightings. As is seen, the pulse envelope alone does not give too good results, neither does the IFV alone (although better than the envelope). A combination of both, with most weight on the envelope, seems to give the best results.

While wavelet decomposition will compress the features and at the same time act as lowpass filters suppressing noise, too many levels of decomposition will

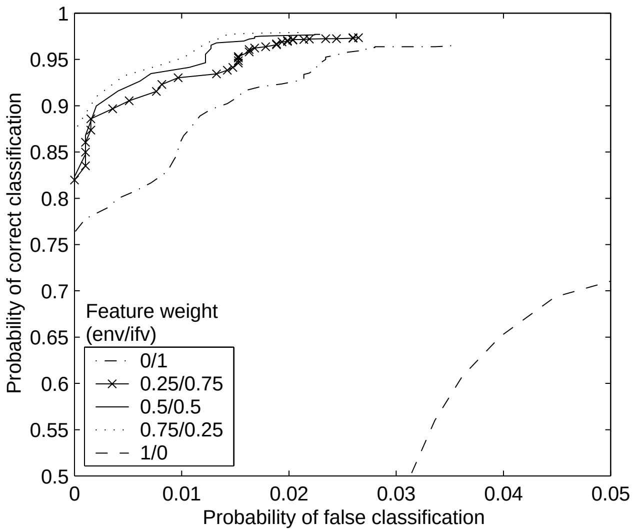

Figure 6: ROC curve for classification using different feature weighting. 4 level wavelet decomposition, 2nd order reverse biorthogonal wavelet used for envelope, 3rd order reverse biorthogonal for IFV.

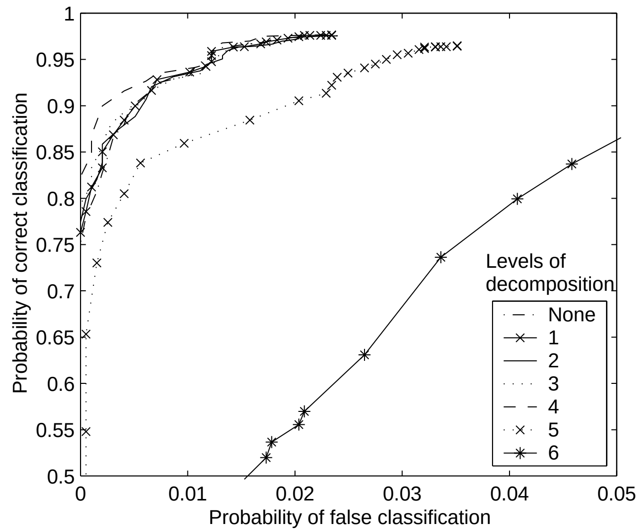

Figure 7: ROC curve for classification using different levels of wavelet decomposition. 2nd order reverse biorthogonal wavelet used for envelope, 3rd order reverse biorthogonal for IFV. Feature weighting is 0.5/0.5 (env/IFV).

also remove the characteristics we are looking for. The classification results will then worsen. Figure 7 shows this effect. 4 levels of decomposition appears to be optimal for the current data set and wavelets.

4. CONCLUSION

This paper proposes a two-stage radar pulse classifier based on intrapulse features. The first stage limits possible classes through pulse width and carrier frequency. The second stage uses pulse envelope and IFV. The test results are promising, showing best results when both envelope and IFV features are used, with envelope weighted heavier than IFV. The features have been compressed using wavelet decomposition which also seems to improve the classification result for certain wavelets. Best results on the current data set were obtained using 4 level wavelet decomposition with 2nd order and 3rd order reverse biorthogonal wavelets for envelope and IFV, respectively.

More data is needed for better confidence in the results and to see if the classifier is capable of specific emitter identification. For emitter identification, additional features and high SNR demands may be required. Further work is also needed to study the effect of choosing a wavelet for feature compression.

More details can be found in [7].

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