An Empirical Evaluation of PDW Extraction Techniques Against Weak LPI Pulsed Radar

Ryan White, Colin Horne, Matthew A. Ritchie
Department of Electronic and Electrical Engineering,
University College London, WC1E 6BT, London, UK.
ryan.white.23@ucl.ac.uk

***Abstract*— Pulse Descriptor Words (PDWs) are a fundamental output of a Radar Electronic Support Measures (RESM) System, they record key features of received radar pulses which can be used to detect and classify radar systems, and if necessary, deploy active protection measures. This paper focuses on three different techniques of varying complexity used to extract PDWs from both simulated and real I/Q samples, and compares their accuracy at extracting pulse width and centre frequency at a range of signal-to-noise ratios (SNR). Comparative techniques are applied in parallel using a digital Instantaneous Frequency Measurement (IFM) receiver on the time domain I/Q samples and two time-frequency methods: the Short Time Fourier transform (STFT) and Wigner-Ville distribution (WVD) in conjunction with the Hough transform. Results show that the greatest accuracy of extracted features was achieved using the IFM receiver at high SNRs down to +6dB and then the Smoothed Pseudo WVD / Hough method down to -15dB SNR.**
***Keywords*— Radar, ESM, ELINT, Software Defined Radio.**

I. Introduction

The ability to detect and identify Radio Frequency (RF) signals is an ever growing challenge, today's Electromagnetic Environment (EME) is now utilised by more and more devices which emit a diverse range of signal types covering a wide range of centre frequencies and bandwidths. This presents significant difficulties in developing methodologies that are able to process these signals and successfully identify their characteristics in this challenging EM environment.

Many modern commercial and military radars operate in a "Low Probability of Intercept" (LPI) mode and spread energy in time and frequency to avoid interception by adversaries, [1]. One such example of an LPI waveform is the "Frequency Modulated Continuous Wave" (FMCW) pulse, which linearly sweeps between two frequencies at a set chirp rate. The spread spectrum and low peak power nature of FMCW pulses makes blind detection and characterisation challenging.

Whilst RESM systems intrinsically have a one-way propagation advantage over the target radar system, the inability to blindly perform processing such as pulse integration or matched filtering to increase the signal-to-noise ratio (SNR) means that in many scenarios, the received pulse may still be buried in the background electromagnetic noise.

Detecting and extracting pulse parameters in these scenarios is challenging for traditional crystal video and Instantaneous Frequency Measurement (IFM) receivers, underscoring the motivation to explore signals through time-frequency transforms for improved detection and estimation of parameters [2] whilst balancing computational complexity. The fusion of time-frequency transforms and image processing techniques is one area where this is possible.

Recent advances in RF receiver hardware have enabled multi giga-sample per second (Gs/s) captures across multiple channels, for example the Xilinx RFSoC (Radio Frequency System-on-a-Chip) features up to 16 ADC/DAC channels with samples rates up to 9.85Gs/s [3]. The capture of large bandwidths of the RF spectrum increases the quantity of data that needs to be processed, leaving a strong requirement on advanced Digital Signal Processing (DSP) methods to handle the throughput.

Previous work has documented the process of extracting radar pulse parameters using time-frequency and Hough transforms [4] [5], this paper focuses on a quantitative comparison of both time domain and time/frequency PDW extraction methods on a mixture of simulated and real data. The objective of this processing was to extract the pulse width and centre frequency of each FMCW pulse and understand the accuracy of this estimation as a function of both applied method as well as SNR. Signal processing methods were applied in both the time domain using a digital IFM receiver and in the time-frequency domain, utilising the Short-Time Fourier Transform (STFT) and Pseudo Wigner-Ville Distribution (PWVD) in conjunction with the Hough transform.

The remainder of the paper is structured as follows, Section II covers the signal domains and extraction methods, Section III defines the datasets used, Section IV presents the results and finally Section V concludes the work.

II. Signal Domains for Feature Extraction

A. Time Domain

The first step for pulse extraction in the time domain is to compute the magnitude of each I/Q sample to verify if it exceeds the pulse detection threshold, a similar threshold is also used to detect the end of the pulse when the magnitude of the signal decays back into the background noise. Careful consideration is necessary when choosing the optimum threshold so that the full duration of pulses are successfully detected and noise is not falsely classified as a pulse.

In the implementation tested in this paper, the pulse trigger threshold was set four standard deviations above the

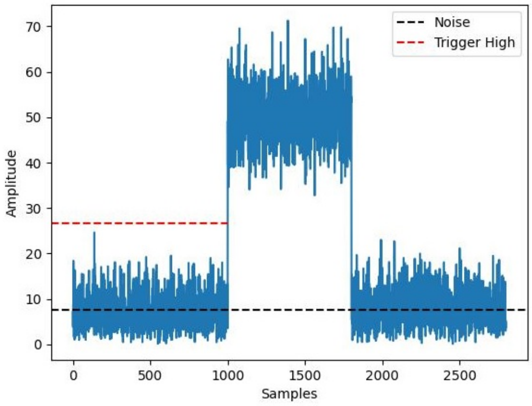

Fig. 1. Adaptive Pulse Trigger Threshold

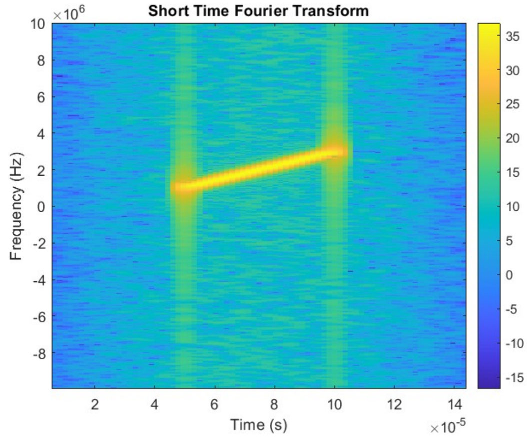

Fig. 2. STFT of a Simulated FMCW Radar Pulse

mean noise magnitude as shown in Fig. 1. The start of a pulse was triggered when the average magnitude over 5 consecutive samples exceeds this threshold, providing a balance of detection sensitivity and resistance to false alarm.

In addition to the pulse width, another important parameter of a detected pulse is the centre frequency. Radar Warning Receivers (RWRs) typically use an analogue IFM receiver to calculate frequency using the phase difference between the incoming signal and a delayed variant of the signal. In this paper a digital equivalent is used which differentiates the instantaneous phase of the IQ signal with respect to time (the sampling interval) to extract the frequency at a given instance [6], this is then averaged over the length "N" of the pulse to give an approximation to the centre frequency when noise is present. This implementation is given by the equation below.

$$Frequency_{avg} = \frac{1}{N}\sum_{i=0}^{N}\frac{d}{dt}\arctan\left(\frac{Q(t_i)}{I(t_i)}\right) \tag{1}$$

B. Frequency Domain

1) The Short-Time Fourier Transform (STFT)

The STFT is a common time-frequency transform, a graphical example of which is shown in Fig. 2. It builds upon the Fourier transform by segmenting a signal into a set of overlapping windows. The Fourier transform is then computed across each window thus allowing the frequency content of a signal to be tracked across time. For low-SNR signals, the output of the STFT allows for the energy of structured signals (e.g. FMCW chirps) to be detected due to the focusing in the frequency-time space.

The discrete variant of the STFT can be given as:

$$STFT(m,\omega) = \sum_{n=0}^{N-1} x(n)w(n-m)e^{-j\omega n} \tag{2}$$

A key parameter of the STFT is the length of the analysis window. Short windows provide good time resolution, but lack sufficient samples for precise estimation of a signal's frequency content. Conversely, large windows give good frequency resolution at the expense of time resolution.

The trade-off between time/frequency resolution is problematic for pulse parameterisation techniques that rely on time-frequency distributions to extract both pulse length and frequency content.

2) The Pseudo Wigner-Ville Distribution (PWVD)

The limitations of the STFT have led to interest in alternative time-frequency transforms that offer improved time and frequency resolution simultaneously.

One of the many alternative time-frequency transforms is the "Wigner-Ville Distribution" (WVD) which achieves a greater time and frequency resolution over the STFT. It involves computing the Fourier transform of the ambiguity function [2].

The main drawback of using the WVD is the introduction of "cross-terms" in the output when multiple signals are present [7]. Modified Wigner-Ville Distributions such as the "Smoothed Pseudo Wigner-Ville Distribution" (SPWVD) aim to suppress cross-terms by using independent window functions to smooth in time ($g(t)$) and frequency ($H(f)$).

The formula for the discrete SPWVD is given below:

$$SPWVD(m,\omega) = \sum_{m=-N+1}^{N-1} x(n+m)x^*(n-m) \\ w_t(m)w_f(k)e^{-j\omega n} \tag{3}$$

C. Hough Space

The Hough transform is a computer vision technique that is used to detect lines in images [8]. It functionally integrates across each possible line in an image and is therefore effective at concentrating intensity in a 2D distribution to a point in the Hough parameter space, enabling the detection of tones and linear chirps down to low SNRs in the time-frequency domain.

Before the Hough transform is applied, typically a median filter is used to smooth out noise but preserve edges [9] and then a binary threshold or edge detection method is used to isolate features as shown in Fig. 3. In some cases, morphological thinning may also be applied to reduce the features, allowing a more accurate Hough line estimation.

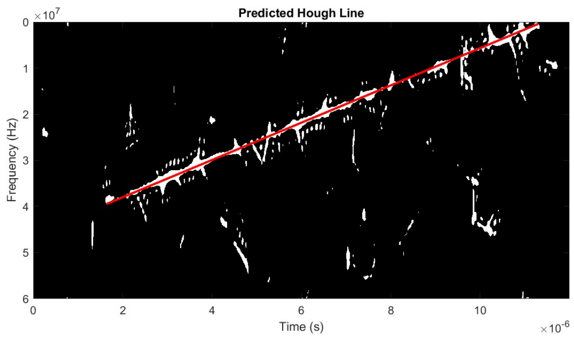

Fig. 3. Median and Binary Filtered PWVD with Estimated Hough Line

In the instance where only one pulse is present in the processed time-frequency transform, the strongest point in the Hough feature space (Fig. 4.) can be used to reconstruct a line of set gradient and distance from the origin, the start (x_1, y_1) and end points (x_2, y_2) are estimated by using the binary filtered thresholds from the original image.

In a realistic threat scenario where multiple chirps may coexist in the same time-frequency spectrogram, iteratively identifying multiple Hough peaks and their associated lines allows for the detection of chirps that overlap in time and frequency, a capability that is not possible with a typical IFM receiver.

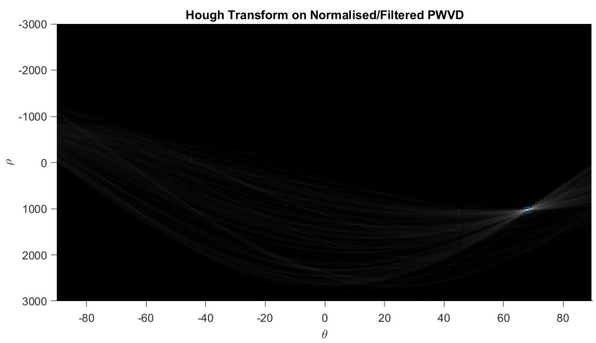

Fig. 4. Hough Feature Space for Fig 3

To extract the pulse width, the difference between the estimated (x) coordinates of the line is multiplied by an x-axis scalar. Similarly, multiplying the mid-point of the y coordinates by the y-axis scalar gives the centre frequency.

In Figure 3, the predicted line from the Hough transform in Figure 4 is shown. Inspection of the x and y axes shows that this is a linearly frequency modulated pulse with width approximately 10 μs and bandwidth of 40 MHz.

Careful consideration is essential when choosing the image filtering thresholds to achieve good parameter extraction accuracy at both high and low SNR. Aggressive filtering ensures good accuracy at high SNRs but may cause truncation or omission of valid pulses at low SNRs. Exploring the performance trade-offs against a representative calibration dataset is essential in ensuring acceptable performance.

After systematically evaluating a range of parameters, it was determined that for the STFT/Hough method with a window length of 512, the best overall estimation accuracy was achieved by applying a 3x3 median filter, setting the binary filtering threshold to 0.5, and performing one pass of morphological thinning. Similarly, for the WVD/Hough technique, the optimal estimation accuracy on the simulation dataset was obtained using an 8x8 median filter and a binary threshold of 0.25.

III. Datasets

A. Simulated Data

To test the three PDW extraction techniques, a library of around 15,000 baseband I/Q samples was generated at 120 Ms/s. The library simulates a set of linearly frequency modulated pulses across 11 different centre frequencies with the SNRs spanning from -15 to +21dB in 3dB increments.

B. Real Data

The experimental data utilised in this paper was generated, transmitted and captured using the UCL ARESTOR system (shown in Fig. 5) which is built around the Xilinx RFSoC, specifically the ZCU111 development board. The ARESTOR system provides an 8 channel transmit/receive capability which is expandable to multiple frequency ranges using custom daughter boards [10].

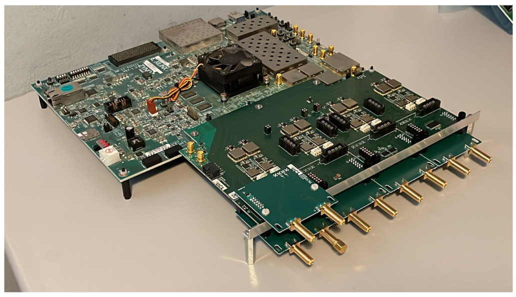

Fig. 5. The UCL ARESTOR System

One ARESTOR node was used to transmit a index modulated sequence of FMCW pulses of varying centre frequency and bandwidth over-the-air while a second node captured these pulses. The pulses were sampled at 3.84 Gs/s on a single channel, mixed down to baseband and then decimated by a factor of 32 to achieve a functional 120 Ms/s final sample rate for offline processing. The SNR was then degraded for each pulse from +21dB to -15dB in 3dB steps, giving a dataset of around 280,000 pulses.

IV. Results

A. Pulse Width Estimation Accuracy

Shown below in Table I is the percentage pulse width estimation error of each technique against SNR for the simulation and experimental datasets.

Table 1. Pulse Width Estimation Percentage Error

SNR	Simulation			Experimental		
	IFM	STFT	PWVD	IFM	STFT	PWVD
21	0.525	-2.740	-1.012	0.568	-3.216	-1.514
18	0.449	-2.792	-1.021	0.525	-3.219	-1.523
15	0.396	-2.767	-1.043	0.454	-3.005	-1.537
12	0.333	-2.912	-1.064	0.439	-3.259	-1.441
9	0.094	-3.037	-1.096	1.231	-3.306	-1.587
6	-10.277	-3.165	-1.135	-9.312	-3.360	-1.636
3		-3.465	-1.222		-3.357	-1.707
0		-3.858	-1.389		-4.033	-1.850
-3		-4.155	-1.784		-4.393	-2.020
-6		-5.616	-1.462		-4.521	-2.303
-9		-6.514	-1.417		-5.991	-2.507
-12		-9.902	-3.813		-12.201	-3.511
-15			-8.937			-10.503

B. *Simulation Dataset Results*

Table II below shows the corresponding percentage centre frequency estimation error of each technique against SNR for both datasets.

Table 2. Centre Frequency Estimation Percentage Error

SNR	Simulation			Experimental		
	IFM	STFT	PWVD	IFM	STFT	PWVD
21	-0.462	-0.025	0.413	-0.528	-0.230	0.520
18	-0.368	-0.039	0.371	-0.465	-0.338	0.540
15	-0.330	-0.071	0.284	-0.414	-0.291	0.561
12	-0.475	-0.018	0.235	-0.487	-0.355	0.514
9	-1.519	0.014	0.227	-1.500	-0.219	0.596
6	-4.627	0.021	0.203	-5.435	-0.396	0.590
3		0.013	0.126		-0.098	0.599
0		-0.021	0.192		-0.733	0.620
-3		0.014	0.721		-1.243	0.598
-6		-0.54	0.619		-1.766	0.931
-9		-2.920	2.538		-2.460	2.499
-12		-6.390	4.433		-15.268	4.294
-15			8.390			9.043

C. *Combined Results*

By combining the absolute pulse width and centre frequency percentage error, the plot of total percentage error for both datasets can be generated as shown below in Fig. 6.

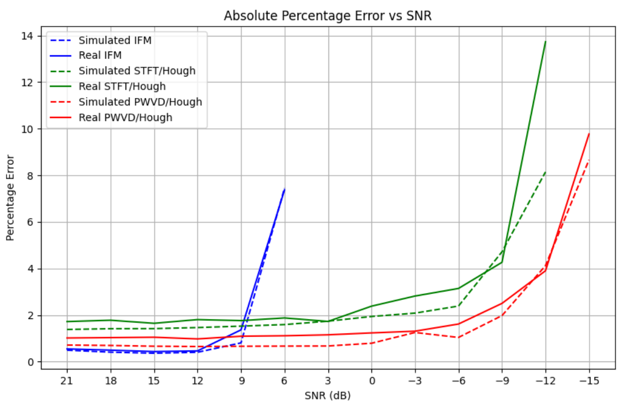

Fig. 6. Combined Feature Estimation Percentage Error

V. Conclusion

The blended simulation and experimental results have demonstrated that at SNRs down to +6dB the pulse width and centre frequency can be reliable extracted directly from the I/Q samples using an IFM receiver.

At lower SNRs, the IFM technique fails to differentiate valid pulses from noise, however the STFT and PWVD based Hough methods are still able to reliably extract pulse parameters down to -12dB and -15dB respectively when a pulse is localised in the spectogram, below this some false parameters are estimated but a clustering algorithm at the pulse descriptor level may be able isolate the correct parameters.

Comparing the two time frequency methods analysed, the PWVD achieved a greater accuracy at the expense of computation efficiency, with each 1500 sample acquisition taking on average 0.78 seconds to process and estimate the detected pulse parameters, whereas the STFT based method and the IFM method took 0.007 and 0.015 seconds respectively. In many scenarios, the requirements for efficient processing may outweigh the benefits of increased resolution in time and frequency. All methods performed similarly on simulation and experimental data, with some discrepancies likely to stem from non-ideal frequency response in the RF chain of the transmit and receive nodes, leading to intra-pulse variations in the magnitude and thus SNR.

Acknowledgment

This work was funded by the Engineering and Physical Sciences Research Council (EPSRC) and the Defence Science and Technology Laboratory (Dstl) through an iCASE studentship.

References

[1] S. Robertson, Practical ESM Analysis, Boston: Artech House Publishers, 1998.

[2] B. Willetts, M. Ritchie, and H. Griffiths, “Optimal Time-Frequency Distribution Selection for LPI Radar Pulse Classification,” IEEE Xplore, Apr. 01, 2020, doi: 10.1109/RADAR42522.2020.9114598.

[3] "Xilinx, Zynq UltraScale+ RFSoC", https://www.xilinx.com/products/silicon-devices/soc/rfsoc.html

[4] T. O. Gulum, A. Y. Erdogan, T. Yildirim and L. Durak Ata, "Parameter extraction of FMCW modulated radar signals using Wigner-Hough transform," 2011 IEEE 12th International Symposium on Computational Intelligence and Informatics (CINTI), Budapest, Hungary, 2011, pp. 465-468, doi: 10.1109/CINTI.2011.6108551.

[5] D. L. Stevens and S. A. Schuckers, “Detection and Parameter Extraction of Low Probability of Intercept Radar Signals using the Hough Transform,” Global Journal of Researches in Engineering, pp. 9–25, Jan. 2016, doi: https://doi.org/10.34257/gjrejvol15is6pg9.

[6] T. W. Fields, D.L. Sharpin, and J. B. Tsui, “Digital channelized IFM receiver,” Dec. 2002, doi: https://doi.org/10.1109/mwsym.1994.335120.

[7] California Institute of Technology, “Time-Frequency Analysis: Wigner-Ville Distribution, Reduced Interference Distribution and Other Methods”, http://case.caltech.edu/tfr/.

[8] Carnegie Mellon University, "Hough Transform - Computer Vison",

[9] University of Edinburgh, "Spatial Filters - Median Filter", https://homepages.inf.ed.ac.uk/rbf/HIPR2/median.htm

[10] M. Ritchie, N. Peters, and C. Horne, “Joint Active Passive Sensing using a Radio Frequency System-on-a-Chip based sensor,” IEEE Xplore, Sep. 01, 2022. https://ieeexplore.ieee.org/abstract/document/9905049/ (accessed Aug. 13, 2023).