A neural based radar detection and classification network

SRED Project #4

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1 BACKGROUND

1.1 SRED Objectives

SCIENTIFIC OR TECHNOLOGICAL OBJECTIVES

WLAN hotspots in the vicinity of airports can interfere with sensitive radar detection circuits. There is a requirement called “Dynamic Frequency Selection” which requires the circuitry to be able to detect a variety of radar pulses with different characteristics and classify them correctly. This information is used to disable WLAN circuits from transmitting interfering signals which may disrupt sensitive RADAR receivers.
The technological objective of this project was to develop a radar pulse classification algorithm which can be implemented in digital signal processing hardware which achieves better than 99% classification accuracy and less than 1% false detection probability. This accuracy represents a technological objective that is much more difficult than presented in any standard and is a significant challenge since there are many different radar pulse signatures, with over 15 different pulse widths, 21 different pulse repetition frequencies, and over 100 different repetition period times.

SCIENTIFIC OR TECHNOLOGICAL ADVANCEMENT

Several “Boolean” type classification algorithms were tried, but none could achieve the stated objective. Finally, a classification algorithm based on a multi-layer feedforward neural network was implemented which closely achieved the objective. The technological advancement obtained is that it is now possible to utilize such trained networks to achieve radar detection and classification accuracies far more greater than previously thought.

SCIENTIFIC AND TECHNOLOGICAL UNCERTAINTIES

Although the neural network achieves excellent classification accuracy, it is not very flexible once it is trained. It is uncertain if future radar signatures will be classified with the accuracy obtained with the first set of radar signature types. The challenge and uncertainty is to be able to design a network which is capable of detecting these pulses with the required accuracy, but is also flexible enough to work when unknown radar signals with different signatures are applied in the future.

SCIENTIFIC AND TECHNICAL CONTENT.

A set of Matlab programs and simulations were constructed to test out the following methods: (a) a “Boolean” based classification network using simple Boolean logic gates (b) a neural based classifier. The two networks were analyzed to provide a performance and complexity tradeoff matrix since the intended target could be either a DSP chip or a digital block implemented in an FPGA or digital ASIC.

1.2 Timeline on DFS requirements for 802.11

This classifier study was started as a result of the timeline for requirements. According to ref [1] equipment must have a robust operation with DFS. For equipment that operates in the 5250 to 5350 MHz band, but does not operate in the 5470 to 5725 MHz band, that was certified prior to January 18, 2006 without DFS and TPC, may continue to be marketed until January 18, 2007.

1.3 System DFS Requirements

Dynamic frequency selection is required as described in 802.11h.
The system requirements can be summarized as follows;

Table 1. DFS Frequency bands.

Item	Units	Min	Typ	Max	Notes
Frequency band 1	MHz	5250		5350	
Frequency band 2	MHz	5470		5725	

Table 2. DFS requirements.

Item	Units	Min	Typ	Max	Notes
Nominal Detection threshold	dBm	-62		-64	Gain setting #1
Low detection threshold	dBm		-75		Gain setting #2
Detection speed	us			1	Actual measurement performed in digital BB. Nominal gain is supplied in calculation of RSSI power levels.
Analog RSSI accuracy	dB	-65		6	For the radio portion only. The digital baseband estimation adds another 1dB to this specification.

The radar signals have the following signatures;

Table 3. **Fixed Frequency Radar Systems**

Parameter Type	Pulse Width (usec)	PRF	Number of Pulses	Burst Period (seconds)	Min pass/fail ratio	Aggregate pass/fail ratio[1]
1-Fixed	1	700	18	10	60%	75%
2- Variable	1,2,3,4,5	500, 600, 700, 800, 900, 1000	23-29	10	60%	75%
3- Variable	6,7,8,9,10	1100, 1200, 1300, 1400, 1500	19-25	2	60%	75%
4- Variable	11, 12, 13,14,15	1600, 1700, 1800, 1900, 2000	17-22	2	60%	75%

Table 4. **Hopping Frequency Radar Systems**

Parameter Type	Pulse Width (μs)	Pulse Repetition Frequency	Pulses per Hop	Burst Period (seconds)	Aggregate pass/fail ratio
1 - Fixed	1	3000	9	10	70%
2 - Variable	1, 2	1400, 1500, 1600, 1700, 1800, 1900, 2000	20	10	70%

[1] As measured over several bursts.

2 DFS PROPOSAL

2.1 Overview

The number of possible radar signatures and the time scales involved means that a conventional correlation function is impractical.

This documents proposes a DFS solution as follows;

- There will be no special hardware in the analog radio to support DFS.
- During DFS periods, the analog AGC's in the LNA and baseband should be forced to an appropriate level to accurately place a -62dBm signal impinging on the antenna at the ADC at a level of -19dBFS. -62dBm somes from the spec [1].
- An optional setting for the analog AGC's could be provided to allow for higher or lower detection thresholds.
- The RSSI level is calculated by performing a power measurement in digital baseband in conjunction with the AGC gain settings, which are known a-priori.
- The digital baseband will pass the I/Q data to a Radar Pulse characterizing block followed by a classification network.

2.2 Block Diagram

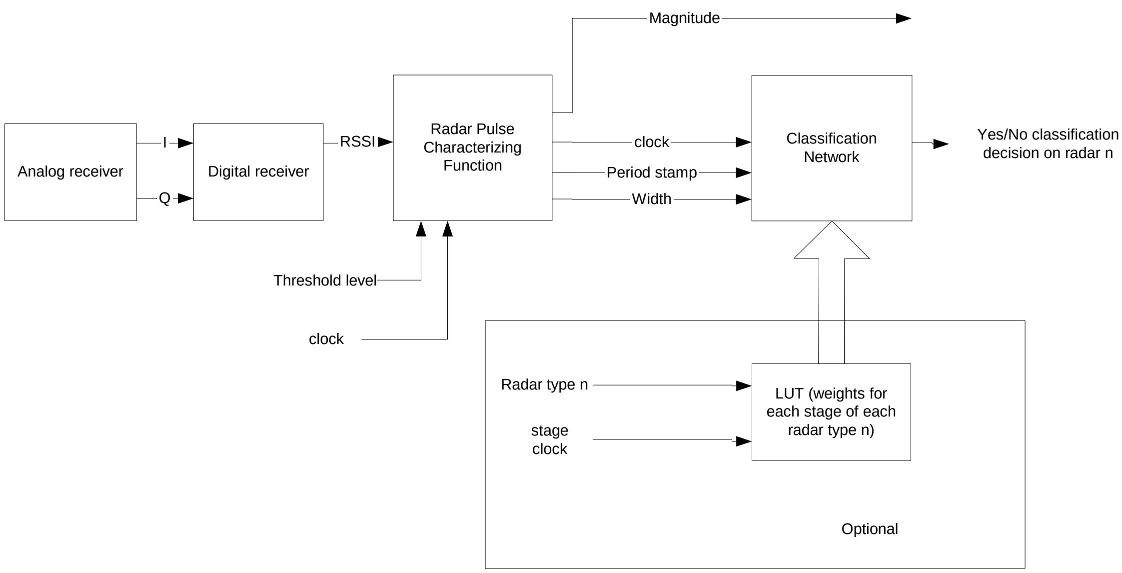

Figure 1 **DFS block diagram**

2.3 Description of the radar pulse characterizing function

This block takes the RSSI information from digital baseband and processes the magnitude, length of time the RSSI stays above the DFS threshold level, and the pulse width (pulse widths are on the order of 1-5us). It also assigns a time stamp to this output and possibly the number of pulses detected within this time width.

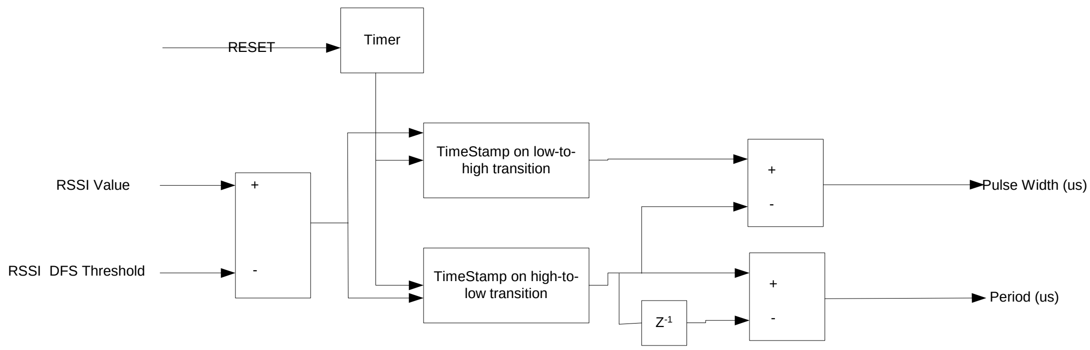

Figure 2. **Radar pulse characterization function.**

2.3.1 Complexity of the characterizing function

Table 5. **Complexity of the characterizing function.**

Item	**Quantity**	**Number of Gates [K]**	**Notes**
Adders/subtractors	3	1.5	Capable of a 10,000 difference at output
storage	1	0.25	Single delay for estimating period.
timers	1	0.1	Capable of counting up to 10,000 us.
Time latches	2	0.5	
TOTAL		2.35K	

3 CLASSIFIER OPTIONS

This information is passed to the nonlinear classifier which will be required to detect the absence or presence of a particular radar signature with aggregate pass/fail ratios listed in [1].

A look up table contains the pre-computed weights for each stage of the classifier, and for many different radar signatures.

3.1 Neural Network Classifier

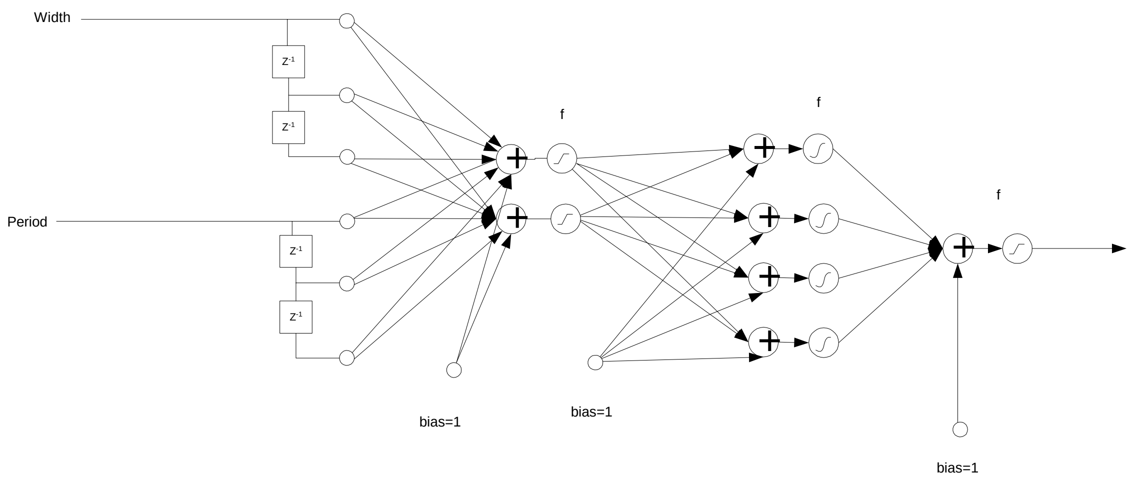

Figure 3 **Generic tapped-delay-line temporal Neural Network Classifier.**

3.1.1 Description of the classifier

The classifier is a simple feed-forward multilayer neural network with pre-computed weights to minimize hardware area. Tapped delay lines on the inputs can be used to give the network memory and make it more robust to missed pulses.

3.1.2 Calculation of weights

The Matlab Neural Network toolbox was used to adaptively train a multilayer feedforward network with sigmoid or saturated nonlinearities using test data.

3.2 Digital Classifier

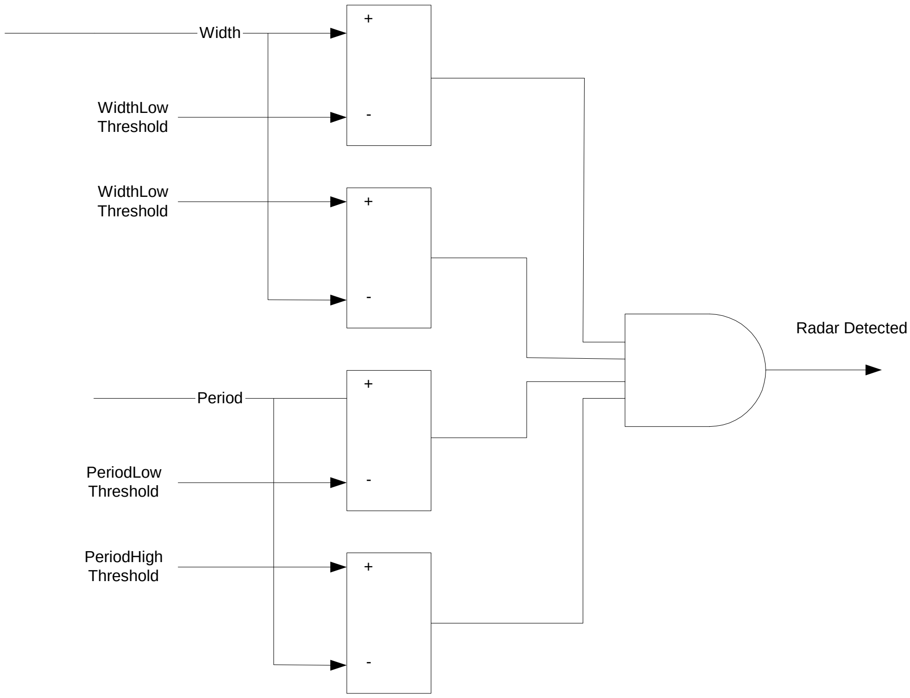

Figure 4. Simple digital classifier.

3.2.1 Description

The digital classifier is a simple engine that determines if the pulse width and period are within a predefined window. If both the pulse width and the pulse period are within acceptable limits, the output classifies as TRUE.

3.3 Counter Block

3.3.1 Description

The counter block is basically an integrate and dump function which takes successive decisions from the classifier and the “Period Detect Pulse” from the detector and applies them to logic. This block performs the following actions;

- A counter counts up to “m” pulses of the “Period Detect Pulse” to generate a reset signal for the I&D.
- The I&D integrates the number of “TRUE” classifications in “m” pulses.
- The output of the I&D is compared to “k”, the minimum number of correct classifications out of “m” pulses detected.
- “*k*” and “*m*” are parameters passed to the block.

The output of the summation block will be required to detect the absence or presence of a particular radar signature with aggregate pass/fail ratios listed in [1].

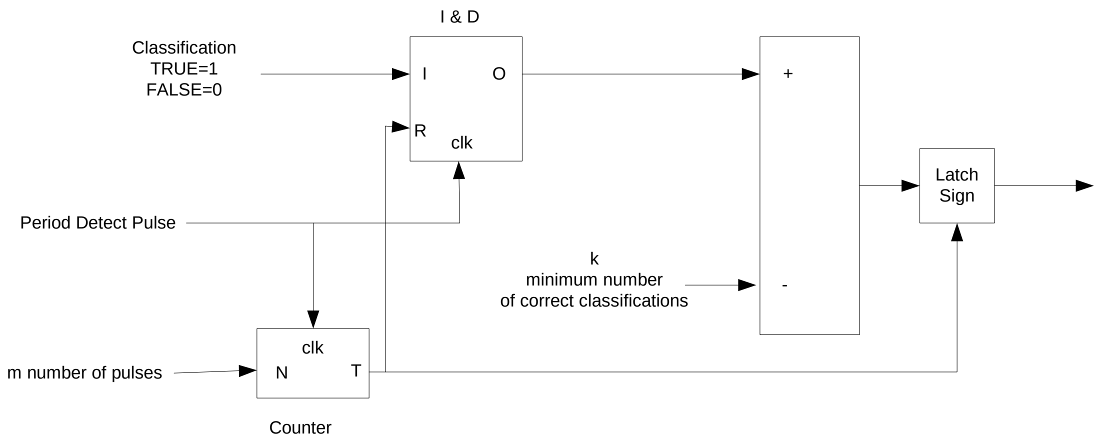

Figure 5. Summation block generates a TRUE output if more than "*k*" correct classifications are obtained out of "*m*" period detects.

3.3.2 Specifications

Table 6. Classifier Specifications

Item	Units	Min.	Typ.	Max.	Notes
"*m*" counter requirements		1	32		
"*k*" counter requirements		4	10	32	

4 CLASSIFIER TRAINING DATA

Training data was generated using the values in Table 3 and Table 4. These values had random noise and jitter added. In addition, false data was also incorporated into the training data. The false data was constructed according to Table 7.

Table 7. False data characteristics.

Parameter Type	Pulse Width (usec)	PRF
Variable	1,2	3500, 3600, 3700, 3800, 3900, 4000
Variable	16, 17, 18, 19, 20	3500, 3600, 3700, 3800, 3900, 4000
Variable	16, 17, 18, 19, 20	100, 200, 300, 400, 500
Variable	20, 21, 22,23,24,25, 26, 27, 28, 29, 30	100, 200, 300, 400, 500

4.1 Training Data

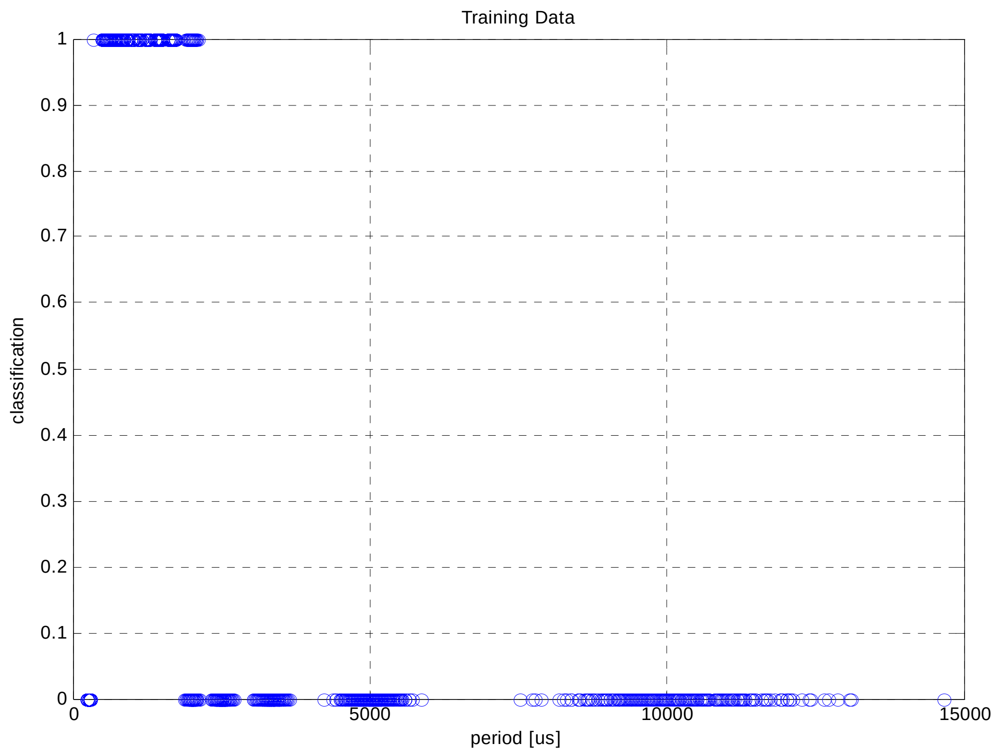

Figure 6. Target training data versus period.

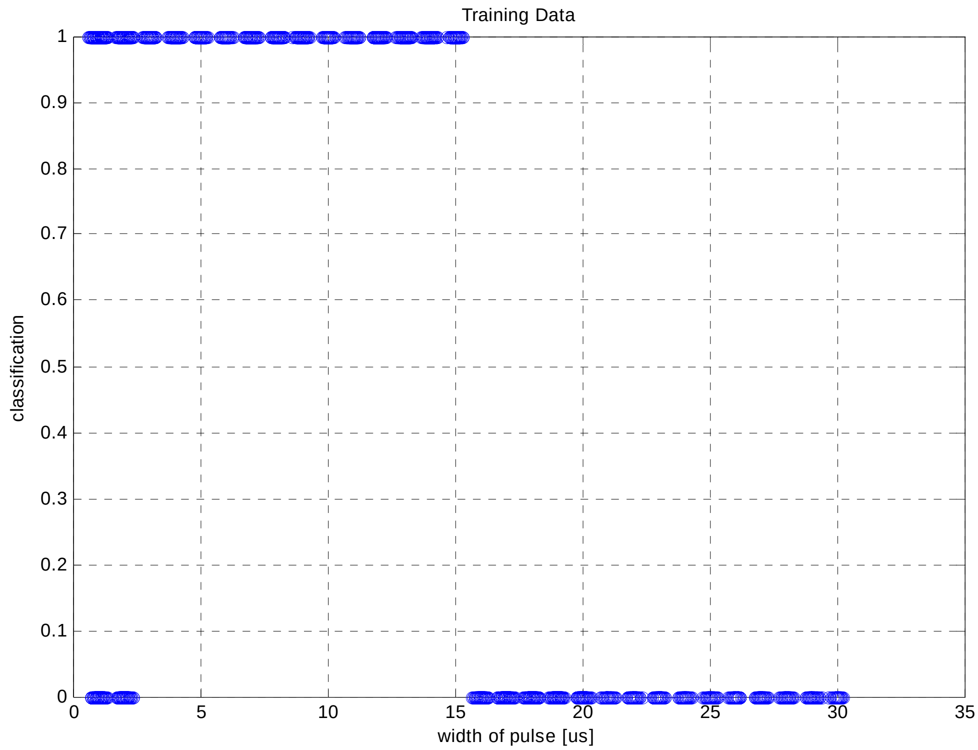

Figure 7. Target training data versus width of pulses.

5 CLASSIFIER TEST RESULTS

5.1 Neural Network : trial3_jan18: [10,10] (7,3,1) [tansig,tansig,purelin]

5.1.1 Description

This used 10 delays in both the width and period inputs and thus has many input layer weights. The internal nonlinear functions are hyperbolic tangents, and the output is a pure linear output.

5.1.2 Error Rate

The error rate was 0.14% error rate.

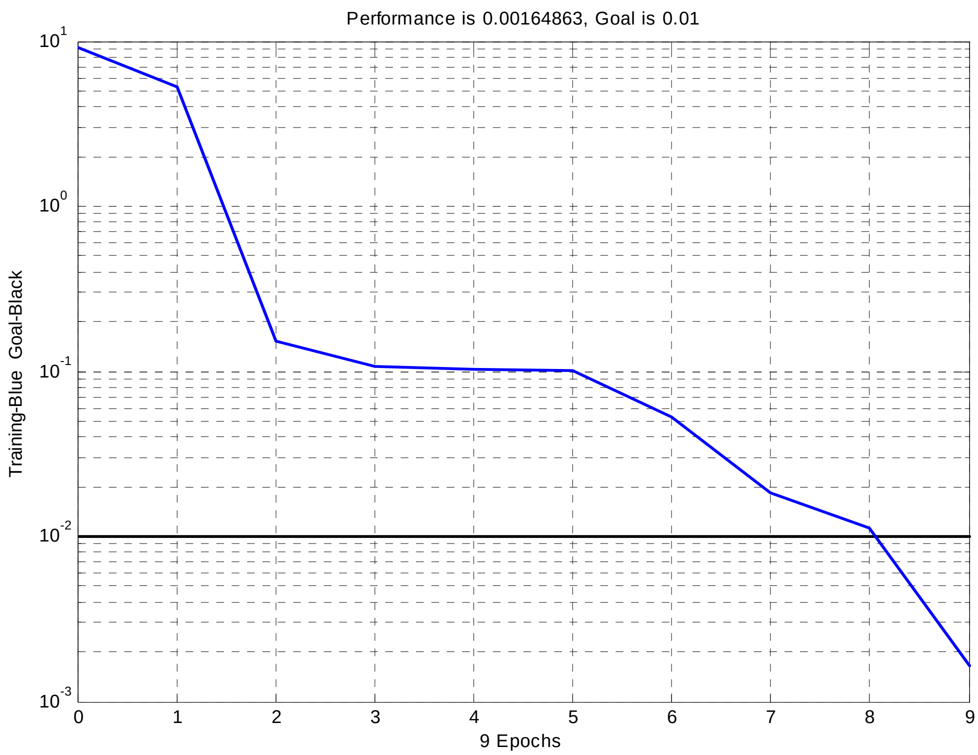

Figure 8. Typical MSE training curve for the neural network classifier.

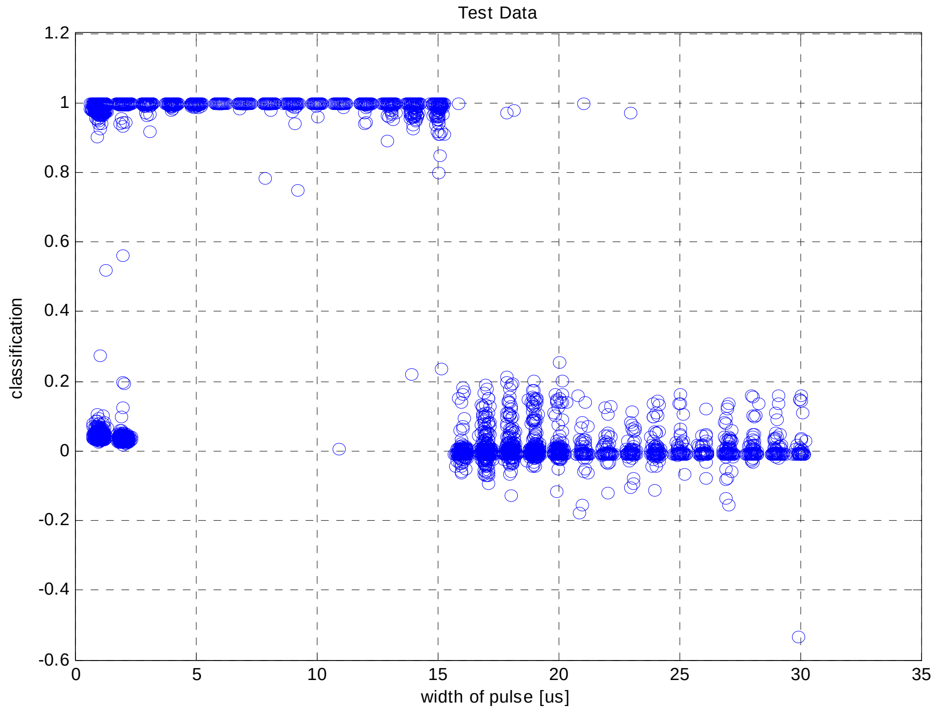

Figure 9. **Test results for the TDL-NN classifier vs. pulse width.**

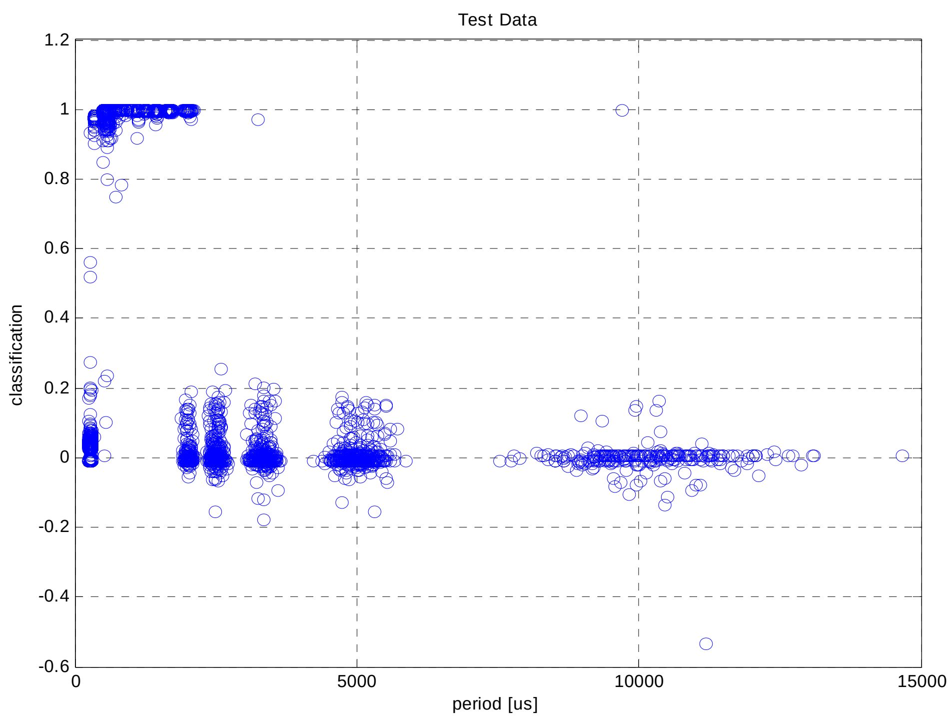

Figure 10. **Test results for the TDL-NN classifier vs. pulse period.**

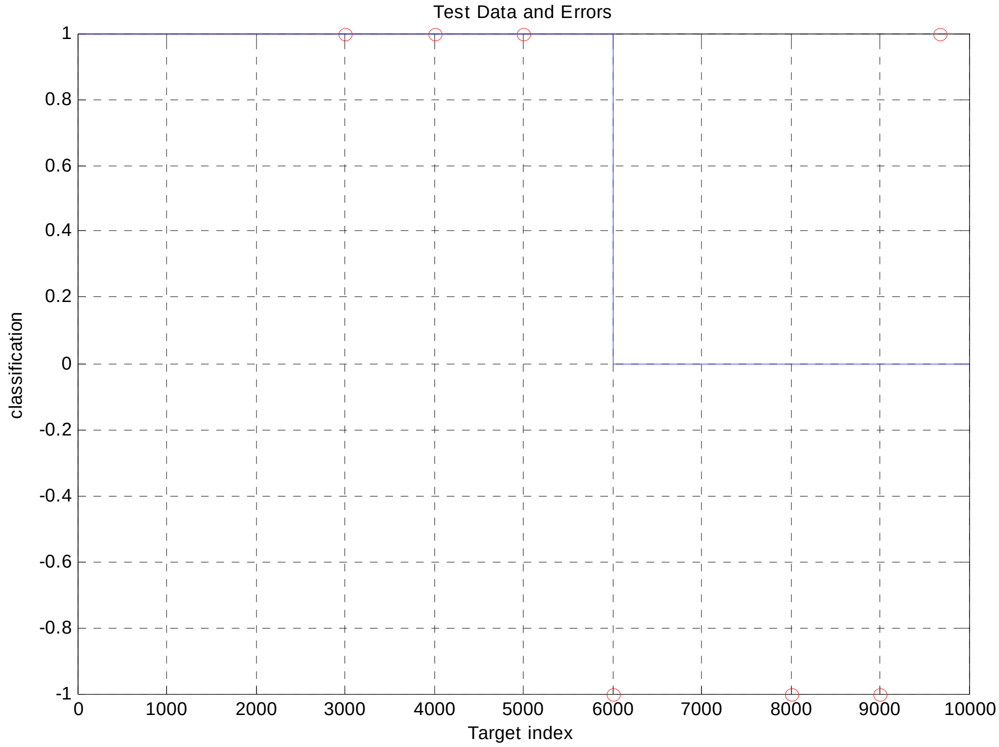

Figure 11. Error performance for the TDL-NN classifier.

5.1.3 Neural Classifier Complexity

Table 8. TDL-NN classifier complexity.

Item	Quantity	Number of Gates [K]	Notes
Adders	11	1.9	
Fixed Real Multipliers	163	50.6	Biases can be hardwired into the adders so are not required as multiplies.
Hyperbolic tangent function	10	5	Implement as a 32 value LUT
TOTAL		55.5K	

5.2 Neural Network: trial7_jan18: [1,1] (2,4,1) [satlin,tansig,satlin]

5.2.1 Description

In order to reduce the number of multipliers, the tapped delay line length was minimized to 1 and number of 1st layer neurons was reduced.

5.2.2 Error rate

The error rate was 0 for this network.

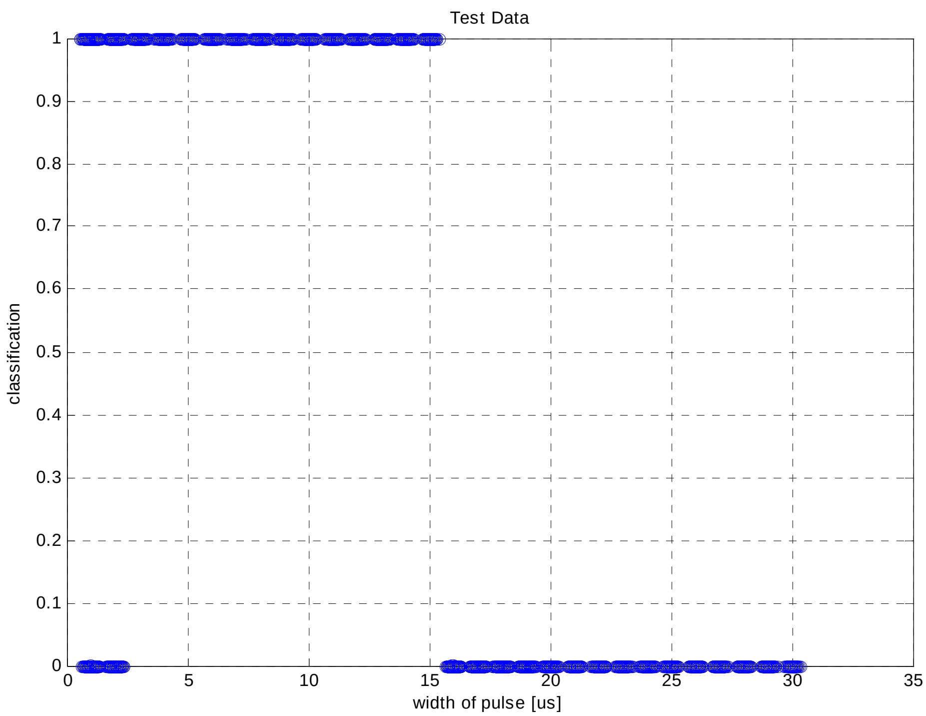

Figure 12 Test results for the NN classifier vs. pulse width.

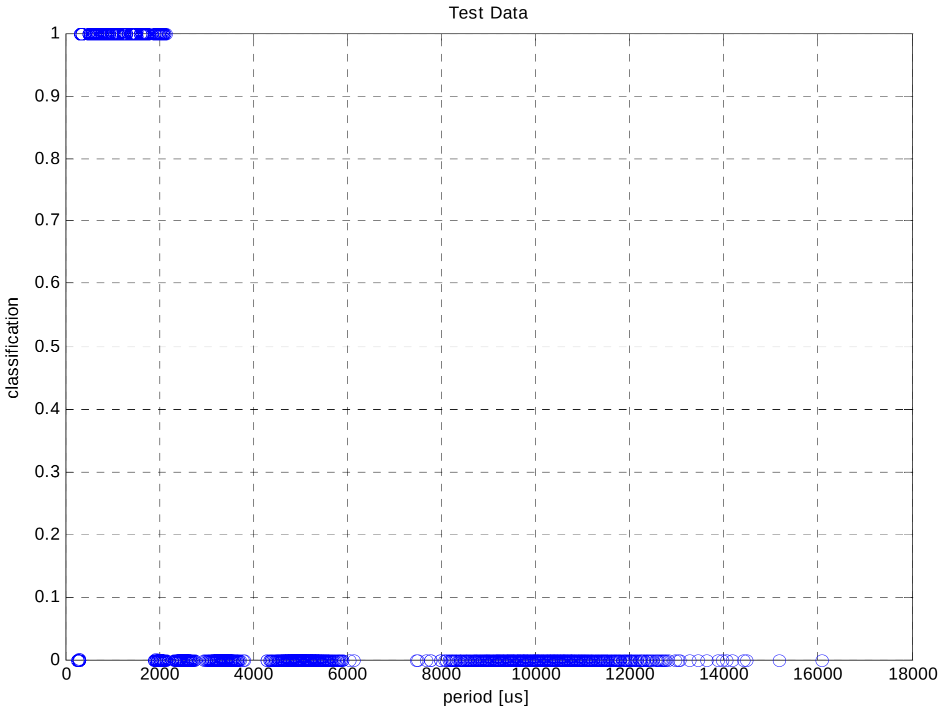

Figure 13. Test results for the NN classifier vs. pulse period.

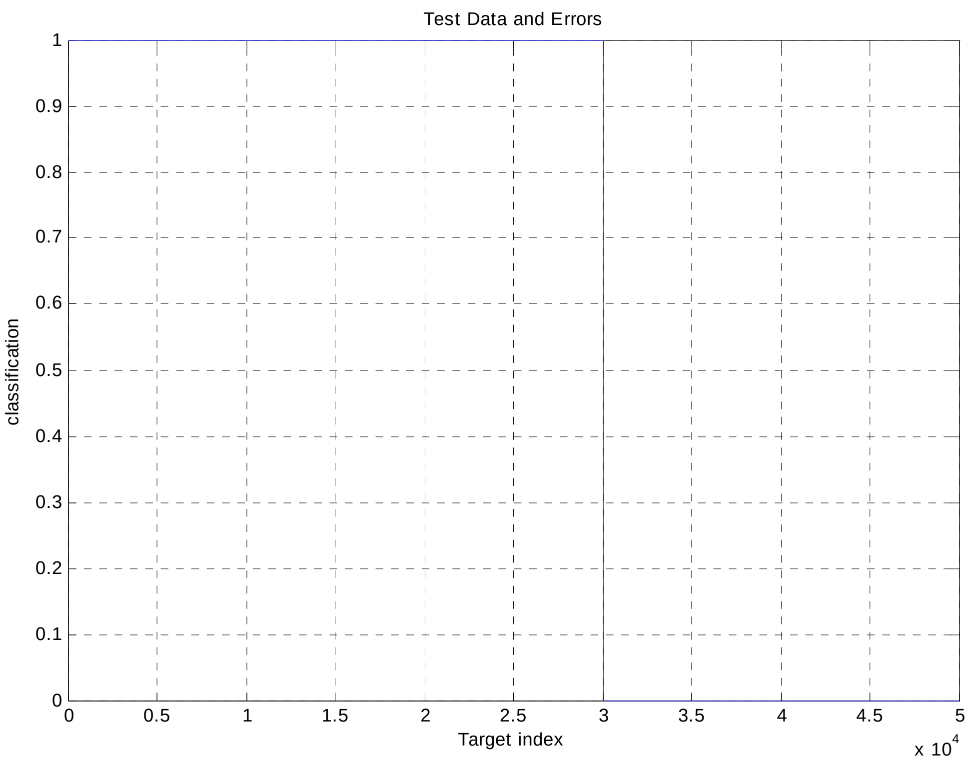

Figure 14. Error performance for the NN classifier –No errors detected.

5.2.3 Trail7_jan18 Network Description

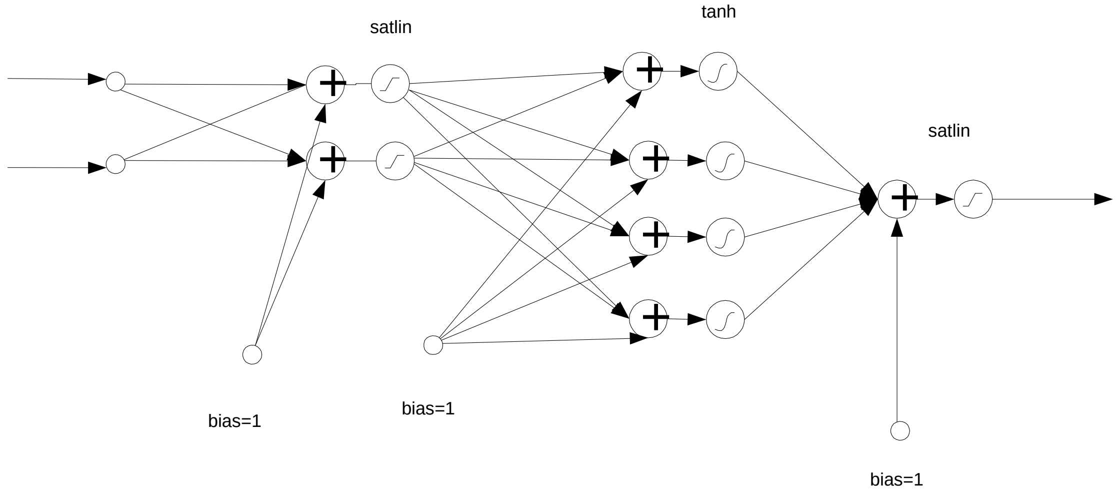

Figure 15. **Simplified NN architecture.**

Table 9. **Trained weight and bias values.**

Weight Matrix	Values	Notes
Input Weight Matrix	-0.0322 -0.0002 -0.0150 0.0048	
Middle Weight Matrix	3.5233 4.1848 -3.0723 4.7276 5.6401 -0.8692 5.4420 -1.3259	
Output Weight Matrix	0.4591 0.8274 0.6565 -0.0227	
Input Bias Matrix	1.1222 -0.7458	
Middle Bias Matrix	-6.8747 -0.4739 -1.2095 0.7258	
Output Bias Matrix	0.1464	

5.2.4 Neural Classifier Complexity

Table 10. Complexity of the simplified NN classifier.

Item	Quantity	Number of Gates [K]	Notes
Adders	7	1.2	
Fixed Real Multipliers	16	5	Biases can be hardwired into the adders so are not required as multiplies.
Saturated Linearity	3	0.1	Simple clipping above 1, below 0
Hyperbolic tangent function	4	2	Implement as a 32 value LUT
TOTAL		8.3K	

5.3 Simple digital classifier

5.3.1 Description

Here we propose a simpler network, consisting of four comparators, and four AND gates.

The architecture is shown in Figure 4.

5.3.2 Error Rate

The network did not perform as well as the Neural Classifier and achieved a 5.79 % error rate on the test data. However, the architecture is much simpler.

5.4 Test Results

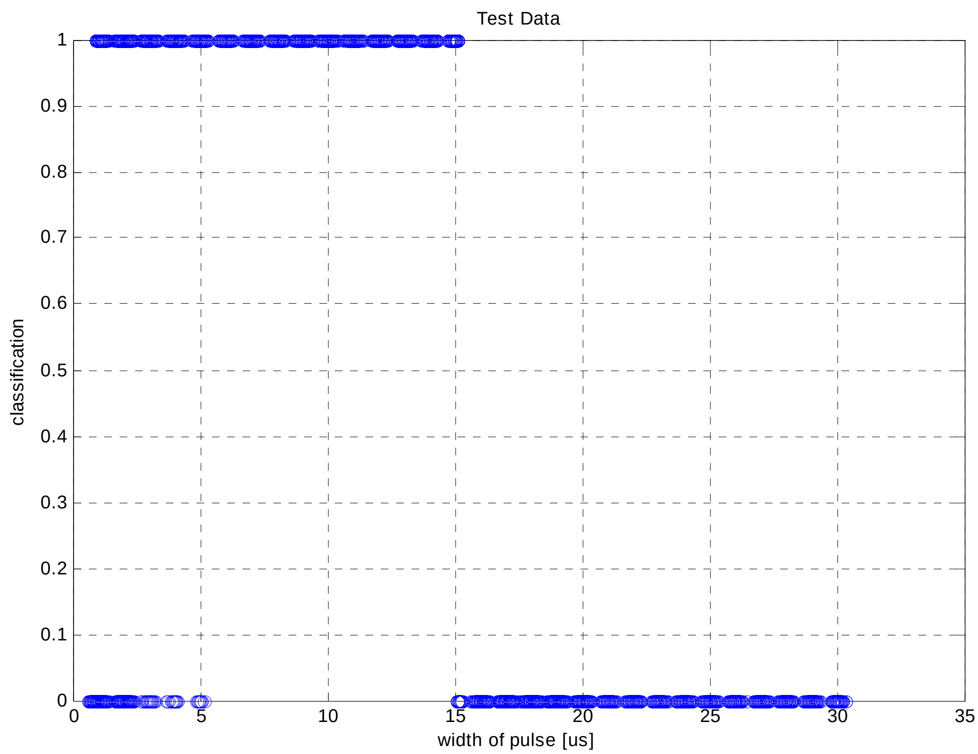

Figure 16. Test results for the DIG classifier vs. pulse width.

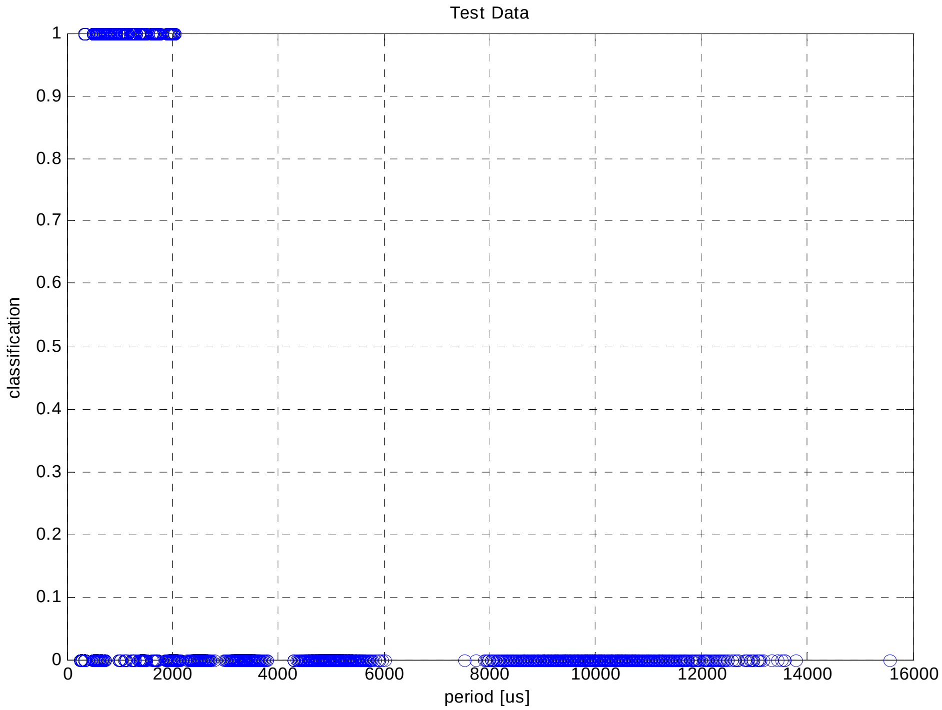

Figure 17. Test results for the DIG classifier vs. pulse period

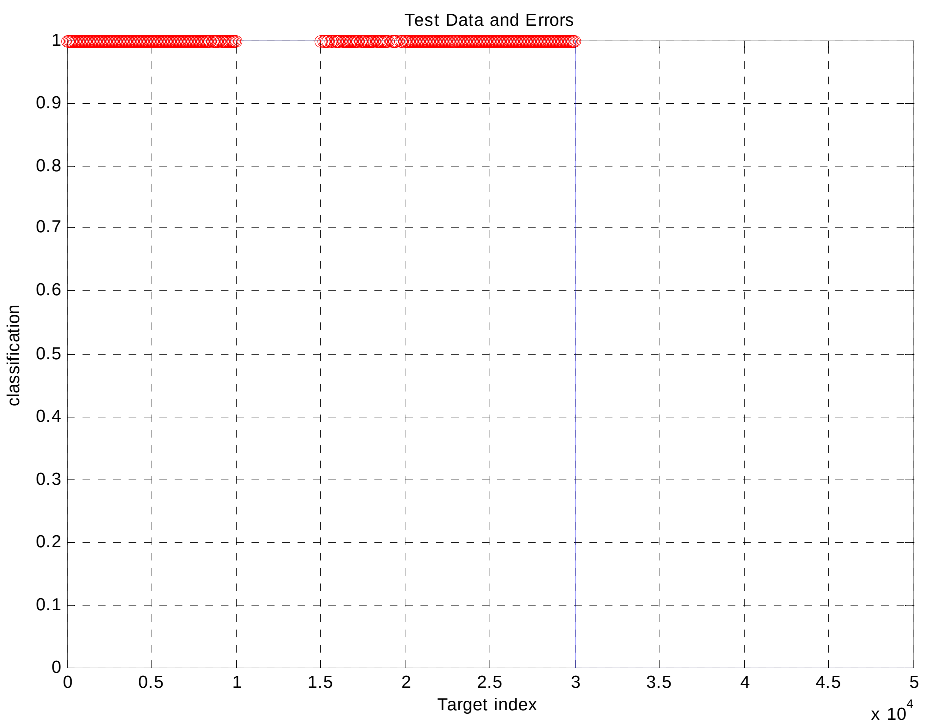

Figure 18. Error results for the DIG classifier. Red indicates an error.

5.4.1 Digital Classifier Complexity

Table 11. Digital classifier complexity.

Item	Quantity	Number of Gates [K]	Notes
Adders	4	0.7	
Loadable thresholds	4	1	
TOTAL		1.7K	

6 SUMMARY

Table 12. Summary of results.

Type	Network	Approximate Complexity[2] [Kgates]	Classification Error [%]	Notes
Neural	[10, 10] tapped delay line (7,3,1) [tansig,tansig,purelin]	57.85	0.14	Very tolerant to noise on input data, and missed radar pulses. Complicated.
Neural	[1, 1] tapped delay line (2,4,1) [satlin,tansig,satlin]	10.65	0	Very tolerant to noise on input data
Digital	Simple comparator/AND	4.05	5.8	Simplest structure and will meet requirements

7 PROBLEMS

The neural network has a tendancy to fall into local minima, and sometimes the solution was not found. Further work is necessary to determine the cause and propose a possible solution.

[2] Includes the 2.35K gates for the radar characterization function.

8 DISCUSSION

- The tapped delay line neural network (TDL-NN) classifier is the most complicated network, requiring 58K gates. However, it has very good accuracy and is tolerant to both noisy inputs and missed radar pulses due to the memory of the TDL.

- It is possible to reduce complexity by implementing a recursive calculation of the network weight matrices. We can do this because of the long time available between radar pulses (on the order of milliseconds). At this point, I do not know how much savings in gates would be obtained using this technique.

- The neural network (NN) classifier without the TDL is very tolerant to noisy inputs and achieved 100% classification accuracy (0% error). However, it does not have any memory and therefore operates on one pulse at a time. The advantage is that it is more efficient than the TDL classifier.

- The digital (DIG) classifier is the simplest network with a complexity of only one-tenth of the TDL-NN and one-half the NN classifier.

- Given that we only require an aggregate 75% accuracy, the simple digital classifier is probably the best choice at this time.

- Further testing in more sever environments may be warranted before making a final choice.

9 APPENDIX

9.1 Definitions

Table 13. Definitions.

Acronym	Definition	Meaning
DFS	Dynamic Frequency Selection	The ability of a radio to detect and avoid co-channel operation of WLAN stations with civil and military radars operating in any 802.11xx channels in the 5GHz band
RPI	Receiver Power Indicator	A quantized measure of the received power level as seen at the antenna connector, which is used to generate statistics of the received signals
TSF	Timing Synchronization Function	The time at which a particular measurement is instructed to start, or actually starts. It has a range of +/- 32 seconds.
TPC	Transmit Power Control	A feature added to 802.11systems to help reduce the amount of interference across all channels and with satellite services operating in the 5GHz band. A stations ability to adapt to a specific RF transmit power level is based on path loss and RF link margin calculations
TU	Timing Unit	1 TU=1024us

9.2 Relevant Standards

- IEEE 802.11a, 1999. Wireless LAN Medium Access control and Physical Layer specification. High Speed Physical Layer in the 5GHz band.
- IEEE 802.11h. Wireless LAN Medium Access control and Physical Layer specification. Amendment 5: Spectrum and Transmit Power management Extensions in the 5GHz band in Europe.
- ETSI EN 301 893 V1.2.3 (2003-08) Annex D. Broadband Radio Access Networks (BRAN) 5 GHz high performance RLAN Harmonized EN covering essential requirements of article 3.2 of the R&TTE Directive

References

[1] 802.11h specification (DFS),
[2] DFS proposal V0.1, N. Birkett
[3] DFS proposal V0.2 N. Birkett.
[4] GenericGateCount.xls,. Gate count spreadsheet.