INFERRING RADAR MODE CHANGES FROM ELEMENTARY PULSE FEATURES USING FUZZY ARTMAP CLASSIFICATION

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Abstract

A method for radar mode inference using Fuzzy ARTMAP classification is presented. In this method elementary radar parameters, Pulse Width (PW) and Pulse Repetition Interval (PRI) originating from a radar operating in a certain mode is input to a Fuzzy ARTMAP classifier. Radar parameters were simulated at different signal-to-noise ratios (SNRs) to train and evaluate the Fuzzy ARTMAP classifier without prior knowledge of radar operating modes. Thus Fuzzy ARTMAP classification is used in the analysis of radar mode behavior. Training resulted in map field weights with high code compression and broad generalization of the input space. The choice of ARTa categories accurately correlated with the current radar mode input data presented to the classifier. It resulted in a 1.8% error in category choice (radar mode) at worst. Classifier training may be done on data with low SNR as the broad generalization during training will accommodate high SNR data without compromising accuracy during evaluation. Knowledge about the amount of radar modes and mode transition can also be gained by an initial training and evaluation (analysis) process to assign pseudo modes to a particular radar. The resultant modes can then be included into a Fuzzy ARTMAP classifier by increasing the dimension of the predicted output, B to classify both radar class and operating mode.

Keywords: Classification; complement coding; electronic support; electronic warfare; Fuzzy ARTMAP; match tracking; mode inference; parameter detection; pulse descriptor word; pulse repetition interval; pulse width; signal-to-noise ratio

1. Introduction

Electronic Support (ES) operations in the Radio Frequency (RF) domain concerns itself with the ability to search, intercept, track and classify threat emitters. The resulting information is typically used to perform Electronic Intelligence (ELINT) gathering, mission planning, threat avoidance and countermeasure optimization [1, 2, 3]. Modern radar systems in turn aim to operate undetected by ES receivers. These radar systems maintain Low Probability of Intercept (LPI) by utilizing low power emissions, coded waveforms, wideband operation and narrow beamwidths without compromising accuracy and resolution. The complexity and degrees of freedom available to modern radar places a high demand on ES systems to provide detailed and accurate real-time information. Input signals are intercepted at the antenna (or antenna array) and are mixed to a pre-defined Intermediate Frequency (IF) or base band frequency by the receiver RF front end. Emitter waveforms are detected and their properties or features extracted into structures called Pulse Descriptor Words (PDWs) [4, 5, 6]. These PDWs contains values for Pulse Repetition Interval (PRI), Direction of Arrival (DOA), carrier frequency, Pulse Width (PW), Instantaneous Bandwidth (BW) and mission specific waveform coding. Detection of radar emitters in ES receivers is achieved depending on the required PDW parameters needed by a classification system, operator or higher-level sensor fusion systems. Fuzzy ARTMAP is a cognitive neural method combining fuzzy logic [7, 8] and Adaptive Resonance Theory (ART) to create categories of class prototypes to be classified. Fuzzy ARTMAP systems are formed by self-organizing neural architectures that are able to rapidly learn, recognize (or classify), test hypothesis and predict consequences of both discreet and continuous input patterns [9, 10, 11, 12, 13].

1.1. Waveform parameter detection

Algorithms that detect pulsed radar emitter waveforms in the presence of noise are applied. LPI emitter waveforms are exceptionally difficult to detect due to the fact that an intercept receiver must coincide with the emitted signal in space, time and frequency, even if only partially. Furthermore intercepted LPI signals may be sampled at low Signal-to-Noise Ratio (SNR) making it difficult to accurately detect waveform parameters. Pulsed or time-limited radar emitter signals are simulated as sampled time series data at the receiver IF. It is assumed that the ES receiver observation time or *snapshot*, span over multiple pulses with complete intercept. The result of the parameter detection stage is structured into PDWs consisting of PW and PRI data for the classification stage.

1.2. Classification

Conventional classification approaches attempt to decide whether data belongs to a certain predefined class according to required performance or accuracy. In this paper a different classification approach is used. Here the specific radar class is known. The classification goal is to infer radar mode changes by observing the internal dynamics within a Fuzzy ARTMAP classifier while it is operating conventionally. Thus data is presented normally to the classifier, which makes classification decisions. The classifier operates in two modes namely, learning or training mode and evaluation mode. During learning the Fuzzy ARTMAP classifier maps PDW entries onto labeled output class data. Learning causes the *map field* weights to adapt in such a way that it will be able to predict output values during evaluation. During evaluation mode the classifier accepts inputs and predicts output values, which may be used to assess overall classification performance. Here the activation of different categories within the Fuzzy ARTMAP classifier for certain changes in radar mode will be evaluated.

2. Pulsed emitter features

Parameter detection of a pulse train consisting of P pulses is modeled as,

$$y(nT) = \sum_{i=1}^{P} A_i \prod\left(\frac{nT - i\zeta_i}{\tau_i}\right) M_i(nT) + w(nT) \quad (1)$$

where the sample time is $T = 1/f_s$, with sample rate f_s (in Hertz) and n is the sample indices $n = 0, \ldots, L-1$ for a snapshot duration of L samples. The pulse index is denoted by i, A is the absolute pulse amplitude (in Volts), ζ is the pulse repetition interval (in seconds) and τ is the pulse width (in seconds). The modulation contained within pulse i is a complex sinusoid for the duration of the pulse (τ).

$$M_i(nT) = \exp^{(j\omega_i nT + \phi_i)} \quad (2)$$

where ω_i is the angular rate (in radians per second) and ϕ_I the initial phase (in radians). The component $w_n(nT)$ is White Gaussian Noise (WGN) with a known variance, σ_n^2. PW and PRI values are detected when the pulse envelope, $E(nT) = |y(nT)|$ crosses a constant detection threshold, D,

$$D = \sqrt{2\log_{10}(P_{fa})\sigma_n^{\,2}} \quad (3)$$

where P_{fa} is the probability of a false alarm within a snapshot. Signal samples above the threshold, D are filtered to discriminate and group pulse rising, n_i^r and falling, n_i^f edge index pairs. Thus pulse width, $\hat{\tau}_i$ is the time between a detected rising edge to the detected falling edge thereafter.

$$\hat{\tau}_i = (n_i^f - n_i^r)T \quad (4)$$

The PRI, $\hat{\zeta}_i$ is the time between a detected rising edge of a pulse relative to the detected rising edge of the previous pulse within the pulse train

$$\hat{\zeta}_i = (n_{i+1}^r - n_i^r)T \quad (5)$$

Finally the PDW data from $i = 1, \cdots, I$ detected pulses are compiled as

$$PDW = \begin{bmatrix} \hat{\tau}_i & \hat{\zeta}_i \\ \vdots & \vdots \\ \hat{\tau}_I & \hat{\zeta}_I \end{bmatrix} \quad (6)$$

3. The Fuzzy ARTMAP algorithm

A Fuzzy ARTMAP system consists of two adaptive resonance theory modules, ART_a and ART_b. The system aims to create stable categories when presented with arbitrary input sequences of data. Both modules are connected via an associative network called the Map Field [14]. Fuzzy ARTMAP control is managed by the map field during learning. The map field ensures that the minimum required recognition categories are formed to meet recognition performance. During supervised learning, input data, $a^{(p)}$ is presented to the ART_a module with the ART_b module receiving, $b^{(p)}$ input data with $b^{(p)}$ representing the correct prediction for a given $a^{(p)}$. Fuzzy ARTMAP is capable of fast learning, efficient and accurate as it co-jointly minimizes predictive error and maximizes predictive generalization using independent internal operations. The ART_a vigilance parameter, ρ_a is adjusted to correct predictive errors in ART_b. ρ_a calibrates the minimum confidence that the ART_a module must have in a recognition category so that $a^{(p)}$ is accepted by ART_a. If this criterion is not met, a search for another category that will meet the criteria is pursued. This criterion is commonly referred to as the vigilance criteria. Small values of ρ_a cause bigger recognition categories to form and implicitly create more generalization and higher code compression. In the event of a predictive mismatch the interconnecting map field sacrifices just enough generalization for the predictive error to be corrected. This process is called match tracking. During match tracking ρ_a is increased by the minimum amount needed to select another ART_a category that will correctly predict $b^{(p)}$ within ART_b. Alternatively another ART_a category is selected which focuses the attention to another set of $a^{(p)}$ inputs that is better suited to predict $b^{(p)}$.

3.1. Fuzzy ART

Fuzzy ART system learning has the advantage of stable learning as weights are monotonically decreasing. This is a useful attribute but can cause category proliferation as many of the adaptive weight values converge toward zero. Complement coding is a pre-processing step that is applied to input data to prevent category proliferation. This method normalizes input data and preserves amplitude information for each feature dimension. Complement coding also ensures that the degree of absence and the degree of presence of input features are contained in the category weight vector, w_j. Normalization of a M-dimensional input vector, **I** is such that for a given $\gamma > 0$,

$$|\mathbf{I}| \equiv \gamma \tag{7}$$

Where $|\cdot|$ is the L_1 *norm* given by,

$$|\mathbf{s}| = \sum_{i}^{M} |s_i| \tag{8}$$

The normalized input vector, **I** is calculated as

$$|\mathbf{I}| = \frac{\mathbf{a}}{|\mathbf{a}|} \tag{9}$$

As mentioned earlier normalization preserves amplitude information. Consequently a complement coded vector includes both the present and absent features of the original vector. The absent features are denoted as a^c where

$$\mathbf{a}^c = 1 - \mathbf{a} \tag{10}$$

Thus an input of dimension M is complement coded into a $2M$-dimensional vector so that

$$\mathbf{I} = (\mathbf{a}, \mathbf{a}_c) \equiv (a_1, \ldots, a_M, a_1^c, \ldots, a_M^c) \tag{11}$$

Fuzzy ART comprises of three layers. The F_0 layer represents the input, **I**. F_1 receives bottom-up input from F_0 and top down input from F_2, which represents the active category. Each layer has its own activity vectors. The F_0 activity vector is $\mathbf{I} = (I_1, \cdots, I_{2M})$ in complement coded form. The F_1 activity is $\mathbf{x} = (x_1, \cdots, x_{2M})$ and the activity vector for F_2 is $\mathbf{y} = (y_1, \cdots, y_N)$. The initial number of nodes in **y** is arbitrary. An adaptive weight vector $w_j \equiv (w_{j1}, \cdots, w_{j2M})$ is associated with each F_2 category node j ($j = 1, 2, \cdots, N$). Categories are said to be committed when it is chosen for coding, otherwise it is uncommitted. Initially the weight values are $w_{j1} = w_{j2} \cdots = w_{j2M} = 1$.The dynamics of a Fuzzy ART system is determined by a choice parameter $\alpha > 0$, a learning rate parameter $\beta \in [0, 1]$ and a vigilance parameter $\rho \in [0, 1]$. Categories are chosen according to the maximum value of the category choice function, $T_j(\mathbf{I})$

$$T_j(\mathbf{I}) = \frac{|\mathbf{I} \wedge \mathbf{w}_j|}{\alpha + |\mathbf{w}_j|} \tag{12}$$

Where $\wedge$ is Fuzzy AND operator with

$$(\mathbf{s} \wedge \mathbf{q})_i \equiv \mathbf{min}(s_i, q_i) \tag{13}$$

If more than one category $T_j(\mathbf{I})$ is maximal, the category with the smallest index j is chosen. Thus categories are committed in order $j = 1, 2, 3, \cdots$. When category J is chosen $y_j = 1$ for $j = J$ and $y_j = 0$ for $j \neq J$. The F_1 activity vector is

$$\mathbf{x} = \begin{cases} \mathbf{I}, & \text{if } F_1 \text{ is inactive} \\ \mathbf{I} \wedge \mathbf{w}_j, & \text{if the } J\text{th node in } F_1 \text{ is active} \end{cases} \tag{14}$$

Resonance occurs if the chosen category J meets the vigilance criteria as follows

$$\frac{|\mathbf{I} \wedge \mathbf{w}_J|}{|\mathbf{w}_J|} \geq \rho \tag{15}$$

Mismatch reset and the search for a category that will meet the vigilance criterion occurs when

$$\frac{|\mathbf{I} \wedge \mathbf{w}_J|}{|\mathbf{w}_J|} < \rho \tag{16}$$

A new category index is chosen according to (12). The previous category T_J is set to zero for the duration of the input presentation so that category J is not chosen repeatedly. Once a category is chosen that meets the vigilance criteria the weight vector is updated (trained) as

$$\mathbf{w}_J^{(new)} = \beta(\mathbf{I} \wedge \mathbf{w}_J^{(old)}) + (1-\beta)\mathbf{w}_J^{(old)} \tag{17}$$

3.2. Fuzzy ARTMAP

The Fuzzy ARTMAP system is the interconnection between two fuzzy ART modules, ART_a and ART_b. The *map field*, F^{ab} links these modules together to form predictive associations between categories and to perform *match tracking* [14]. The interactions between the map field, F^{ab} and other fuzzy ART modules are as follows. Inputs to the ART_a and ART_b modules are $\mathbf{I} = \mathbf{A} = (a, a_c)$ and $I = \mathbf{B} = (b, b_c)$ respectively. Variables and vectors in ART_a and ART_b are denoted by superscript and subscript identifiers, a and b. Then $\mathbf{x}^a \equiv (x^a_1, \cdots, x^a_{2Ma})$ is the activity vector at $F_1{}^a$ and $\mathbf{y}^a \equiv (y^a{}_1, \cdots, y^a{}_{Na})$ is the output vector at $F_2{}^a$. The weight vector for category j in $F_2{}^a$ is $\mathbf{w}^a{}_j \equiv (w^a{}_{j1}, w^a{}_{j2}, \cdots, w^a{}_{j2Ma})$. Similarly for ART_b, $\mathbf{x}^b \equiv (x^b{}_1, \cdots, x^b{}_{2Mb})$ is the activity vector at $F^b{}_1$ and $\mathbf{y}^b \equiv (y^b{}_1, \cdots, y^b{}_{Nb})$ is the output vector at $F^b{}_2$. The weight vector for category k in $F^b{}_2$ is $\mathbf{w}^b{}_k \equiv (w^b{}_{k1}, w^b{}_{k2}, \cdots, w^b{}_{k2Nb})$. The map field, F^{ab} output vector is $\mathbf{x}^{ab} \equiv (x^{ab}{}_1, \cdots, x^{ab}{}_{Nb})$ and the weight vector from the jth $F^a{}_2$ node to F^{ab} is $\mathbf{w}^{ab}{}_j \equiv (w^{ab}{}_{j1}, w^{ab}{}_{j2}, \cdots, w^a{}_{Nb})$. Vectors $\mathbf{x}^a$, $\mathbf{y}^a$, $\mathbf{x}^b$, $\mathbf{y}b$ and $\mathbf{x}^{ab}$ are 0 in between input presentations. The activation of the map field is subject to activity of either ART_a or ART_b. When node J is chosen to activate ART_a, the weights $\mathbf{w}^{ab}{}_J$ activate F^{ab}. When node K activates ART_b, F^{ab} is activated via the ART_b output vector, $\mathbf{y}^b$. When both ART_a and ART_b are active, F^{ab} only becomes active when ART_a

correctly predicts the same ART_b category from $\mathbf{w}^{ab}_J$. The F^{ab} activity or output vector, $\mathbf{x}^{ab}$ has the following possible values

$$\mathbf{x}^{ab} = \begin{cases} |\mathbf{y}^b \wedge \mathbf{w}_J^{ab}|, & \text{if the } J\text{th } F_2^a \text{ node is active and if } F_2^b \text{ is active} \\ \mathbf{w}_J^{ab}, & \text{if the } J\text{th } F_2^a \text{ node is active and if } F_2^b \text{ is inactive} \\ \mathbf{y}^b, & \text{if } F_2^a \text{ is active and } F_2^b \text{ is inactive} \\ 0, & \text{if } F_2^a \text{ and } F_2^b \text{ are inactive} \end{cases} \tag{18}$$

Predictions are confirmed in (18) by producing a single nonzero value in the $\mathbf{x}^{ab}$ vector. Predictions are disconfirmed when all the values in $\mathbf{x}^{ab}$ are zero. Then, the map field responds by initiating a search for a better ART_a category with the *match tracking* process. At the start of each input presentation the ART_a vigilance ρ_a equals a baseline value, $\bar{\rho}_a$ with the map field vigilance parameter, ρ^{ab}. Match tracking occurs when

$$|\mathbf{x}^{ab}| < \rho_{ab} |\mathbf{y}^b| \tag{19}$$

During match tracking ρ_a is increased so that it is slightly greater than $|\mathbf{A} \wedge \mathbf{w}^a_J|/|\mathbf{A}|$ and causes the selected Jth ART_a node not to meet the vigilance criteria as in (16). This leads to a search for another ART_a category, J so that

$$|\mathbf{x}^a| = |\mathbf{A} \wedge \mathbf{w}_J^a| \geq \rho_a |\mathbf{A}| \tag{20}$$

and

$$|\mathbf{x}^{ab}| = |\mathbf{y}^b \wedge \mathbf{w}_J^{ab}| \geq \rho_{ab} |\mathbf{y}^b| \tag{21}$$

If no such a category exists a new uncommitted ART_a category is created and F^a_2 is deactivated for the remainder of the input presentation. Map field learning occurs during resonance when both (20) and (21) are satisfied [14, 15, 16]. The map field weights, $\mathbf{w}^{ab}_J$ change as follows

$$(\mathbf{w}_{jk}^{ab})^{new} = \begin{cases} (1-\beta_{ab})(\mathbf{w}_{jk}^{ab})^{old} + \beta_{ab} x_k^{ab}, & \text{if } j = J \\ (\mathbf{w}_{jk}^{ab})^{old}, & \text{if } j \neq J \end{cases} \tag{22}$$

4. Simulation experiment

In order to exploit inferring of radar mode changes using a Fuzzy ARTMAP classifier the following simulation experiment was conducted. Simulation involves generating radar emissions from a number of modes, sampling the intercepted signals as in (1), detecting the PW, $\hat{\tau}_i$ and PRI, $\hat{\zeta}_i$ parameter values and presenting them to the classifier. Three modes from a hypothetical radar is simulated. These modes are labeled and listed in Table 1. Simulated radar pulse trains are generated according to (1) with PW and PRI parameter values as in Table 1. The sample rate, f_s is 100MHz and each snapshot contains L = 600e3 samples. The noise energy is scaled so that the SNR is constant. SNR is calculated as

$$SNR = \frac{e^{(s)}}{e^{(w)}} \tag{23}$$

where $e^{(s)}$ is the energy of the pulsed signal only, $y(nT) - w(nT)$ and $e^{(w)}$ is the energy in the noise signal, $w(nT)$. A_i is fixed at unity while the noise energy is controlled via σ_n to achieve the desired SNR. Fuzzy ARTMAP classification undergoes two tests. During the first test the Fuzzy ARTMAP classifier is trained on data that was generated at a high SNR and evaluated against data generated with SNR values less or equal to the SNR of the training data. The second test is just the opposite of the first test. Here the Fuzzy ARTMAP classifier is trained on data that was generated at a low SNR and evaluated against data generated with SNR values greater or equal to the SNR of the training data. The inference of a particular radar mode is interpreted as the Fuzzy ARTMAP classifiers' consistent selection of ART_a categories that pertain to inputs from that particular radar mode. Furthermore the Fuzzy ARTMAP classifier has no knowledge of radar mode information in the output prediction data vector, **B**. It is presented to ART_b as a one dimensional vector. Correlation of the selected ART_a categories and the radar mode is made post-evaluation.

Table 1. Radar Mode Table

Label	PW (μs)	PRI (ms)
Mode 1	0.08	0.48
Mode 2	0.3	0.83
Mode 3	0.8	1.67

4.1. Classifier training

Training and evaluation data are generated separately. Data is presented in the form of PDWs described in (6). The training data consists of 3000 pulses for each radar mode. Thus the training data PDW, $PDW^{(T)}$ is a 9000-by-2 matrix. The generation of data is also done at different signal-to-noise ratios (in decibel), $SNR^{(T)}$ = (8, 12). During a training epoch data is presented in a random order until the map field weights, $\mathbf{w}^{ab}_{jk}$ converge or remain unchanged when presented with training data. The Fuzzy ARTMAP parameters for ART_a and $ART_b$are, α = 0.01, β = 1 and ρ = 0.8. The map field learning parameter, β_{ab} = 0.7 and vigilance parameter, ρ_{ab} = 0.99. No limit was placed on the amount of categories that both ART_a and ART_b may commit or create during training. Results of classifier training are presented in Table 2. *Test 1* produced fewer ART_a categories than *Test 2*. This is due to the classifier mapping of higher SNR data as its *frame of reference*. Also a greater amount of code compression is achieved in *Test 1* indicating that the classifier has a more generalized map representing the data. The code compression in *Test 1* is, 1285:1 and 818:1 in *Test 2*. Three epochs was required to achieve convergence in the map field weights, $\mathbf{w}^{ab}_{jk}$ during training in *Test 1*. *Test 2* required five training epochs. The consequence of slower convergence during training is that more ART_a categories are formed and that the distribution of the categories varies substantially.

4.2. Classifier evaluation

Evaluation data is generated as a series of 999 pulses. The radar modes within the data set are equally divided into 333 pulses per mode. The evaluation data is further arranged so that it is presented to the classifier in a sequence. The sequence is made up of 150 pulses in Mode 1, 333 pulses in Mode 2, 333 pulses in Mode 3 and the remaining 153 pulses in Mode 1. Thus the simulated data represents a repeating cycle through the available radar modes. The input data, $PDW^{(E)}$ is a 999-by-2 matrix generated for signal-to-noise ratios (in decibel), $SNR^{(E)}$ = (8, 9, 10, 11, 12). Evaluation results are averaged across SNR.

Table 2. Fuzzy ARTMAP Training and Evaluation Results

Training	Test 1	Test 2
ART_a categories	7	11
ART_b categories	3	5
Category index, Mode 1	2,5	1,2,7,9
Category distribution (%)	45,54	17,39,33,10
Category index, Mode 2	1,6	3,6,8
Category distribution (%)	59,40	32,54,14
Category index, Mode 3	3,4,7	4,5,10
Category distribution (%)	43,51,6	16,27,56
Number of epochs	3	5
Evaluation	**Test 1**	**Test 2**
Average accuracy (%)	98.8	99.2
Incorrect Mode 1 category (%)	1.5	0.6
Incorrect Mode 2 category (%)	1.8	1.5
Incorrect Mode 3 category (%)	0.3	0.3

Both tests produced very accurate classification of the radar class. This was expected as training and evaluation was required for only a single class.

Although the Fuzzy ARTMAP classifier was over-trained (the ratio between training and evaluation data is greater than one) some errors in prediction did occur as the incorrect ART_a category was chosen to make a prediction of the correct radar class value. The percentage incorrect category choice for each radar mode is shown in Table 2. The transitions from Mode 1 through Mode 3 and back to Mode 1 are easily tracked by observing the activation or choice of ART_a categories for each input presentation. For example, when input data is presented to the ART_a module and either category j = [2, 5] is chosen, it relates to the radar operating in Mode 1. When the ART_a category choice index j changes from 6 to 4, the radar mode has changed from Mode 2 to Mode 3. The inference of radar modes can be simplified even further by clustering the ART_a categories into three clusters, with each cluster representing a radar mode.

5. Conclusion

Fuzzy ARTMAP classification was used in the analysis of radar mode behavior. The classifier was trained without any prior knowledge of how many radar modes existed and what the present mode the radar was operating in. Training parameters α, ρ_a, ρ_b, ρ_{ab} were chosen so that the classifier trains more than one category although the classification output was constant. Training resulted in map field weights, $\mathbf{w}^{ab}_{jk}$ with high code compression and broad generalization of the input space. The activation or choice of ART_a categories accurately correlated with the current radar mode, resulting in a 1.8% error in category choice (radar mode) at worst. Fuzzy ARTMAP evaluation accuracy did not differ substantially between the two tests specified in Section 4, considering that data with different SNR was presented to the classifier during both tests. Classifier training may be done on data with low SNR as broad generalization during training will accommodate high SNR data without compromising accuracy during evaluation. Knowledge about the amount of radar modes and mode transition can also be gained by an initial training and evaluation (analysis) process to assign pseudo modes to a particular radar. The resultant modes can then be included into a Fuzzy ARTMAP classifier by increasing the dimension of the predicted output, **B**.

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