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IMPORTANT INFORMATIVE STATEMENTS

A Comparison Study of Radar Emitter Identification Based on Signal Transients

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Abstract— **Radar emitter identification has been studied for decades using library-based techniques that rely on pre-existing knowledge of parameters such as radio frequency (RF), pulse amplitude, pulse width, intentional pulse modulation type, or pulse repetition intervals. However, current radar emitter identification techniques will not be sufficient against cognitive radars due to their parameter agility and adaptability. In this study, five radar emitter identification fingerprints based on radar signal transients were analyzed and compared. These fingerprints include: (1) fractal dimension estimation of signal transients, (2) natural measures of signal transients, (3) polynomial regression of a signal transient energy trajectory acquired by its 4th order cumulants, (4) RF fingerprints based on the energy trajectory characteristics of signal transients, and (5) intrinsic shape of the rising edge of a pulse. The analysis and comparison were performed using *K*-Nearest Neighbours, Quadratic Discriminant Analysis, and relative entropy over a dataset from five different radar emitters. The advantages and drawbacks of each technique are highlighted. Our results show that (2), (4) and (5) achieve very competitive emitter identification performance using the selected radar datasets and classification algorithms. This study also demonstrates that the optimal emitter identification performance is dependent on the combination of RF fingerprints and classification algorithms.**

Keywords — Cognitive radar, radar emitter identification, radar SEI, cognitive electronic warfare, machine learning.

I. Introduction

Radar emitter identification is a special case of the broader Specific Emitter Identification (SEI) for RF devices. The SEI designates the unique RF transmitter of a given signal by comparing its external features with a library of clusters and selecting the cluster that best matches the feature measurements [1]. Radar emitter identification is interested in identifying a particular model of radar while radar SEI is interested in identifying a particular instance of radar of the same model. More advanced radar emitter identification methods can be used for radar SEI.

Conventional radar emitter identification techniques rely on pre-existing knowledge of classical pulse parameters such as radio frequency, pulse amplitude, pulse width, intentional pulse modulation type, or pulse repetition intervals. However, the radar threat environment has changed and will continue to change in the future. Modern radar is becoming more agile in parameters and more cognitive in operations. The current radar emitter identification techniques would not be able to correctly identify cognitive radars due to their parameter agility and adaptability. Therefore, non-classical radar emitter identification techniques are needed in order to counter cognitive radar threats. The new type of cognitive radar emitter identification must be based on the intrinsic and unique features of a radar emitter.

The signal transient (i.e., the rising edge) of a radar pulse contains Unintentional Modulation on Pulse (UMOP) features, which include Unintentional Modulation on Amplitude (UMOA) and Unintentional Modulation on Frequency (UMOF). UMOP features are unavoidable and unique to radar emitters [2]. They are produced by manufacturing errors and intrinsic non–idealities in the hardware components (e.g., filters, frequency mixers, power amplifiers) of a radar emitter, which cannot be avoided by radar system designers and manufactures. As a consequence, UMOP features are particularly suitable to develop an RF fingerprint, which can be used for both cognitive/non-cognitive radar emitter identification and radar SEI.

Many signal transient-based SEI techniques have been proposed and validated using either radar signals or communications RF signals. In [3], a new SEI method based on relative entropy between natural measures of the one-dimensional component of their chaotic systems is proposed; it is based on the observation that the natural measures are different between systems. This SEI method is evaluated using the Automatic Identification System (AIS) signals emitted from ships. In [4], the fractal dimension of a signal transient is presented and used as an RF fingerprint to identify specific RF emitters; this SEI method is validated using Bluetooth signals. Fractal geometry and its extension - multifractals - are new tools which can be used for describing, modeling, and analyzing different complex shapes and signals [5, 6, 7, 8, 9]. In [10], the polynomial fit coefficients of the signal transient energy trajectory and transient duration are used as an RF fingerprint to identify specific RF emitters; the energy trajectory of a signal transient is calculated from the fourth order cumulants of the signal transient. This SEI method is validated using cellphone signals. In [11], six features derived from the energy envelope of a signal transient are used to form the unique RF fingerprint of a radio emitter. These features include the normalized integral, duration, maximum slope, kurtosis, skewness, and variance of the signal transient envelope. This SEI method is validated using Bluetooth signals. All these methods were tested using different RF signals with different signal-to-noise ratios, and each study used different classification methods. For these reasons, it is difficult to directly compare the advantages and drawbacks of each RF fingerprint. In this study, the same radar dataset was used and the signal transient is defined from 5% to 95% of the signal's average peak amplitude.

In this paper, we propose an SEI method that is only based on the intrinsic shape of the signal transient, without making use of any classical pulse parameters. The intrinsic shape of the signal transient is described by a combination of fractal dimension, entropy, skewness, and kurtosis of the signal transient. Then, we compare this method with the aforementioned SEI methods using the same radar signal dataset. The rest of the paper is organized as follows. In Section II, we give a detailed description of each RF fingerprint. In Section III, the selected classification methods are presented. In Section IV, the evaluation results are provided, and advantages and drawbacks of each SEI technique are discussed. Section V concludes the paper.

II. METHODS OF SIGNAL TRANSIENT ANALYSIS

A. Fractal Dimension of Signal Transient

1) Fractal theory

In geometry and topology, a straight line has one dimension; a surface has two dimensions and can be divided by a line; and a space has three dimensions and can be divided by a surface. In one dimensional space, measuring a line using a stick half its size gives a length of $(1/2)^{-1}$ sticks. If another measurement is done using a stick one third its size, the length of the line is $(1/3)^{-1}$ sticks. Similarly in two dimensions, consider a square whose sides are of unit length. If each side of the square is divided in half (i.e., 1/2), then $(1/2)^{-2}$ squares are generated. If each side of the square is divided into thirds, $(1/3)^{-2}$ squares are produced. This scaling relationship holds true to a higher number of dimensions as well. Such scaling relationships can be defined mathematically as follows:

$$\omega = (1/r)^{-D} \tag{1}$$

where ω is the total number of hyper dimensional divisions (sticks in one dimension, and squares in two dimensions), r is the scaling factor, and D is the dimension. By rearranging Equation (1), the dimension D can be expressed as

$$D = \frac{\log \omega}{\log r} \tag{2}$$

In fractal geometry [12, 13], a fractal is an abstract object used to describe naturally occurring objects. It is usually agreed that (deterministic) fractals arise from the repeated iteration of a transformation [6]. In other words, fractals are mathematical objects which could be written as

$$A = \lim_{n\to\infty} \tau^n(A_0) \tag{3}$$

where A_0 is an initial object and τ^n denotes n iterations of the transformation τ.

Fractals exhibit self-similarity [12, 13]. A fractal is said to be self-similar if it can be broken down into arbitrarily small pieces, each of which is a small replica of the entire fractal. This property makes fractals useful in analyzing systems that exhibit recurring patterns at progressively lower scales.

An example of a fractal is the von Koch curve [12, 13]. It is created as follows: let E_0 be a line segment of unit length. The set E_1 consists of the four segments obtained by removing the middle third of E_0 and replacing it by the other two sides of the equilateral triangle based on the removed segment. E_2 is constructed by applying the same procedure to each of the segments in E_1, and so on [12]. The von Koch curve after four iterations is shown in Figure 1.

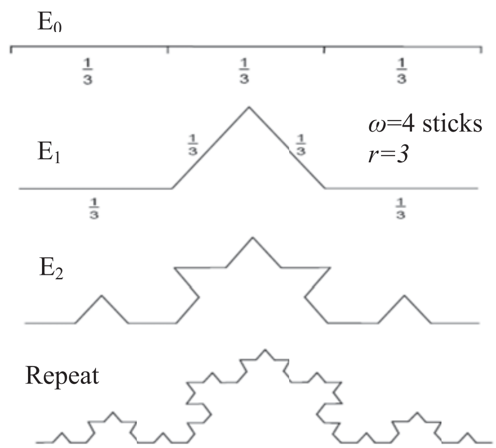

Figure 1. The von Koch Curve.

The fractal dimension is a descriptor that characterizes fractal patterns by measuring the ratio of a dataset's complexity (i.e., length, area, volume) to change in scale. Equation (2) can be extended to calculate fractal dimensions. For example, in the von Koch curve, when ω = 4, its scaling factor is 3, therefore, the fractal dimension of the von Koch curve is

$$D = \frac{\log \omega}{\log r} = \frac{\log 4}{\log 3} = 1.2619 \tag{4}$$

There are different methods for quantifying the fractal dimension of a fractal object [12, 13, 14]. Higuchi's method [7] is a common way to find the fractal dimension of a time series signal in signal processing.

2) Higuchi's fractal dimension

Higuchi's fractal dimension is a measure of the complexity of a time series signal vs scale and is calculated as follows. Consider a signal X, in time, with N samples: $X(1), X(2), X(3), \dots, X(N)$. Define $X(m,h)$ to be the subset of the original signal X according to the following:

$$X(m,h){:}\ X(m), X(m+h), \dots, X\left(m + \left[\frac{N-m}{h}\right] h\right) \tag{5}$$

where m is the sampling point at the initial time, h is the lagging point number in the time interval, and m=1,2,3,…,h.

For each of the $X(m,h)$ subsets, its length can be defined as:

$$L_m(h) = \left(\sum_{i=1}^{\frac{N-m}{k}} |X(m+ih) - X(m+(i-1)h)| \right) \frac{N-1}{\left[\frac{N-m}{h}\right] h} \Big/ h \tag{6}$$

Let $L(h)$ be the average length for each fixed h over all m. Then, we can plot $\log(h)$ versus $\log(L(h))$ and fit a straight line to it using least squares method. The resultant slope is the Higuchi fractal dimension.

3) Fractals and radar signals

In this study, radar pulse signals are modelled as fractals as noisy radar signals in time domain exhibit fractal geometry pattern. The transient energy trajectory (as defined in Eq. (12)) of a signal was extracted and interpolated. Interpolation is needed as some signal transients had few (<20) data points. The trajectory was split into two parts: the first half and the second half based on time. Using Higuchi's method, the fractal dimension of the first half, F_1, the second half, F_2, and entire transient, F_e, were calculated. The resultant three dimensional vector (F_1, F_2, F_e) was used as the RF fingerprint of a radar emitter.

B. Polynominal Regression of Transient Energy Trajectories

Cumulants are used to describe the higher order statistical characteristics of random processes [10, 15, 16]. The cumulants of order greater than two of Gaussian noise are identically zero [16]. Third order cumulants are identically zero when the probability density function of the magnitude of a signal is symmetrical. Therefore, the fourth order cumulants are used to remove the effect of white Gaussian noise while still preserving the signal transient.

To define the cumulants of a zero-mean complex signal $X(i)$, where i=1,2,…,N, and N is the total number of data points in the signal, first consider the p-order hybrid moment:

$$M_{pq}(i) = E[X(i)^{p-q}X^*(i)^q] \tag{7}$$

where * is the complex conjugate operator, q is the number of conjugate placements, $q \leq p$, and E is the expected value operator. For instance,

$$M_{20}(i) = E[X(i)^2],\ \ M_{21}(i) = E[X(i)X^*(i)] \tag{8}$$

$$M_{42}(i) = E[X(i)^2X^*(i)^2] \tag{9}$$

A window centered at $X(i)$ with each left and right side length L is created. Each window has $2L$+1 data points. The average value of $X(i)^{p-q}X^*(i)^q$ in this window is calculated. The resultant average is the estimate of the p-order hybrid moment at $X(i)$.

The signal $X(i)$'s fourth order cumulant with two conjugate placements is defined as follows [10, 15]:

$$C_{42}(i) = M_{42}(i) - |M_{20}(i)|^2 - 2(M_{21}(i))^2 \tag{10}$$

The energy trajectory of a signal transient is defined as follows:

$$y(i) = \sqrt{|C_{42}(i)|} \tag{11}$$

where i=1,2,…,N_{tr}, and N_{tr} is the total number of data points in the signal transient. The use of the fourth order cumulant removes the effect of white Gaussian noise from the signal. Note that the energy concept in this paper is different from the one used in physics or engineering.

The transient energy trajectory is normalized to a value between 0 and 1 according to:

$$y_{norm}(i) = \frac{y(i)-\min(y(i))}{\max(y(i))-\min(y(i))} \tag{12}$$

A polynomial of order 7 was fit onto each signal's y_{norm}. The resultant vector of polynomial coefficients is a fingerprint for that pulse.

C. Entropy and Natural Measures

1) Entropy

In physics, entropy is typically associated with the amount of disorder in a system. In information theory, entropy is defined as the average amount of information produced by a probabilistic stochastic process [17]. A common measure of entropy is the Shannon Entropy Index, H, for a random variable X. For a probability mass function (PMF) $P(X)$, the Shannon Entropy is defined as [17]:

$$H(X) = -\sum_{i=1}^{n} P(X_i)\log(P(X_i)) \tag{13}$$

For example, suppose that you have a box of green balls. The probability mass function of this system with respect to colour X would be: $P_r(X = green) = 1$, $P_r(X \neq green) = 0$. Its H value would be $\log(1) = 0$. According to this H index, no information is encoded in this system. Clearly, the system has no disorder, it is only green. But, the H value would be log(3) if three different color balls were in the box at a proportion of 1/3. There is clearly more information and disorder in the second system.

Using this idea, the relative entropy between two PMFs μ_P and μ_Q on probability space Y is defined as follows:

$$D_{KLD}(\mu_P|\mu_Q) = \sum_{x\epsilon Y} \mu_P(x)\log(\frac{\mu_P(x)}{\mu_Q(x)}) \tag{14}$$

If $\mu_Q(x)$ or $\mu_P(x)$ is 0, the value is changed to 1/N, with N being the maximum number of samples between P and Q signals. This modification of the PMF is divided by the new sum of μ and called the natural measure. The D_{KLD} can be seen as a measure of dissimilarity between two probability mass functions. When $\mu_P = \mu_Q$, $D_{KLD} = 0$. When the two distributions are more dissimilar, D_{KLD} will increase.

2) Entropy and radar signals

The normalized and interpolated y_{norm} of the signal transient is extracted. A PMF can be constructed from the signal transient. The resultant natural measure is the fingerprint. The D_{KLD} is used as a classifier to associate the pulse with a specific emitter (details in section III.C).

D. RF Fingerprints Based on Signal Transient Energy Trajectory

Another fingerprint based on physical and statistical characteristics of the energy envelope was introduced in [11]. In this study the fingerprint was applied as follows. The first characteristic is the duration of the signal transient, D_I, of a pulse. The second is the area under the signal's y_{norm}., A_I. A_I is the accumulation of energy during the transient time. The next characteristic is the maximum derivative (or slope) of the signal's y_{norm}, P_I. P_I is a measure of the peak power used to get the signal from noise to its peak amplitude. Clearly, these physical parameters can be influenced by signal transient duration.

Two statistical values of the signal's y_{norm} were also used. They are skewness, S_1, and kurtosis, K_1. Skewness and kurtosis are given by the following two equations respectively:

$$S_1 = E[(\frac{X-\mu}{\sigma})^3] \tag{15}$$

$$K_1 = E[(\frac{X-\mu}{\sigma})^4] \tag{16}$$

where X is signal's y_{norm} data, μ is the mean of X, and σ is the standard deviation of X. Skewness is a measure of the asymmetry of the PMF of the energy curve. Kurtosis is a measure of how outlier-prone the PMF of the energy curve is. The kurtosis of the normal distribution is 3. Distributions that are more outlier-prone than the normal distribution have kurtosis greater than 3; distributions that are less outlier-prone have kurtosis less than 3.

Now let the σ_1 be the variance of the signal's y_{norm}. The resultant fingerprint is given by the vector (D_1, A_1 , P_1 , S_1, K_1, σ_1). This RF fingerprint is referred to as DAPSKV for short.

E. *Intinsic Shape of Signal Transients*

Lastly, we propose an RF fingerprint that is only based on the intrinsic shape of the signal transient, without making use of any classical pulse parameters. The intrinsic shape of the signal transient is described by a combination of fractal dimension, Shannon entropy (13), skewness, and kurtosis of the signal's y_{norm}. All these features are explained in Section A through D above.

III. Classification Algorithms

A. *K-Nearest Neighbours*

K-Nearest Neighbours (KNN) is a supervised machine learning algorithm [18]. Let $T=\{t(1), t(2), \ldots, t(N_T)\}$, where $t(i)$ is a fingerprint vector for the i^{th} pulse in T, and N_T is the number of pulses. The emitters of each element in T are known. Suppose you have another set of N_U pulses, $U=\{u(1), u(2), \ldots, u(N_U)\}$ with $u(j)$ being a fingerprint vector for the j^{th} pulse in U. The emitters of each element in U are unknown.

KNN classifies $u \in U$ by finding the K elements in T that are closest to u. The K elements are denoted by $T' \subseteq T$. The Euclidean distance was used to measure closeness. The emitter of u is identified to be the emitter that occurs most frequently in T'. If multiple emitters occur most frequently in T', then the emitter of u is assigned to one of them at random.

The KNN can be trained or analyzed by dividing the set T into two sets: training set and testing set. The training set acts as T, and the testing set acts as U. The difference is that the emitter of each element in the testing set is known. To evaluate the KNN classification performance, KNN classifies each element in the testing set by finding the K closest elements in the training set. Since we actually know the emitter for each element in the testing set, the successful classification rate can be measured.

B. *Quadratic Discriminat Analysis*

Quadratic Discriminant Analysis (QDA) is another supervised machine learning algorithm [18]. It first builds a probability density function of the RF fingerprint for each known emitter. Then, it calculates the probability that an unknown pulse fingerprint comes from each of the emitters. The emitter of the unknown pulse is identified according to the greatest probability.

Suppose E is a set of all emitters and X is a set of all pulse fingerprints. Let the probability density function of RF fingerprints, $x \in X$, from a particular emitter, $e \in E$, be $Pr(X=x \mid E=e)$. $Pr(X=x \mid E=e)$ is the probability that a pulse has feature vector x when it comes from radar e. $Pr(X=x \mid E=e)$ is assumed to have a multivariate normal distribution. The mean is estimated by the sample mean, or average, of pulse fingerprints from an emitter e. The covariance matrix is the sample covariance of the pulse fingerprints from an emitter e. A multivariate normal distribution for the pulses' fingerprints from emitter e is:

$$Pr(X = x|E = e) = \frac{e^{-\frac{1}{2}(x-\mu)^T\Sigma^{-1}(x-\mu)}}{\sqrt{(2\pi)^d \det(\Sigma)}} \tag{17}$$

where Σ and μ are the sample covariance matrix and sample mean of pulse fingerprints from emitter e, respectively, $(.)^T$ indicates the transpose operation, $(.)^{-1}$ indicate the inverse operation, d is the dimension of x, and det(.) is the matrices determinant.

Next, define π_e to be the probability of receiving a pulse from emitter e. π_e is estimated by the proportion of data available from radar e. Combining all of these equations we can apply Baye's Theorem to find the probability that an unknown pulse fingerprint, x^* comes from emitter e.

$$\Pr(E = e|X = x^*) = \frac{\pi_e \Pr(X=x^*|E=e)}{\sum_{l=1}^{Ne} \pi_l \Pr(X=x^*|E=l)} \tag{18}$$

In this equation N_e is the number of emitters. An unknown pulse is assigned to the emitter e for which $Pr(E=e| X=x^*)$ is the greatest.

C. *Relative Entropy Measure*

The relative entropy measure is given by D_{KLD} in Equation (14). In order to use the D_{KLD} for classification, a set of normalized transients of amplitude data from a known emitter is required. The normalized transients are binned into s bins that split the interval [0, 1] into s equal parts. The resultant frequency distribution is divided by the total number of data. This creates a probability mass function template (PMFT) for a specific emitter. Each emitter has its own PMFT.

Now consider a pulse from an unknown emitter. Proceed as before and construct a PMF for this unknown pulse's normalized transient, UPMF. Then calculate D_{KLD}(PMFT | UPMF) , Equation (14), for each emitter template and assign the unknown pulse to the emitter whose template gives the smallest D_{KLD} value.

IV. Results

A. *Radar Datasets*

Five different emitter datasets were selected from five different radar emitters. These emitters are labeled as emitter

1, emitter 2, emitter 3, emitter 4, and emitter 5. The pulses from the same emitter have different signal to noise ratios (SNR). Table 1 shows the mean, standard deviation, min, and max values of the SNRs for the 65 pulses (incl. 40 pulses for training and 15 pulses for testing) of each emitter.

Table 1 Summary of Radar datasets.

Emitters \ SNR (dB)	Mean	Standard deviation	min	max
Emitter 1	13.7817	3.6594	7.8504	20.7287
Emitter 2	5.7969	5.9681	-2.8928	25.8040
Emitter 3	1.2484	5.7869	-4.1926	15.2143
Emitter 4	8.7286	11.8656	-6.7701	27.8746
Emitter 5	15.0542	0.0085	15.0340	15.0674

Three normalized cumulants from noise to average peak amplitude for each of the four emitters are plotted in Figure 2. The first emitter is not plotted due to space limitation.

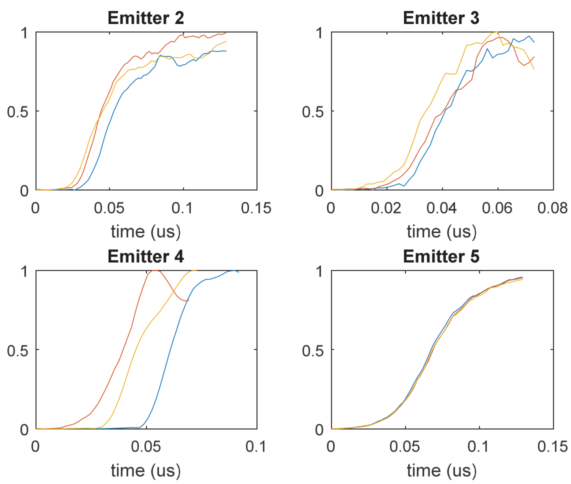

Figure 2. Normalized signal transient energy trajectories of three signals from four emitters.

To compare the performance of all five fingerprints, a Monte Carlo experiment with 2000 simulations was developed. In each simulation, 40 training and 15 testing pulses were randomly selected per emitter; the normalized transients were extracted; the RF fingerprints were calculated, and then the correct identification percentages were computed using each classification algorithm. A linear interpolation (4 points) was applied to calculate the PMF of a signal transient due to the limited number of sampling points.

B. *Results*

For the KNN classification algorithm, the correct identification percentage of the testing data versus the number of neighbours is plotted in Figure 3 for one of the 2000 Monte Carlo simulations. The average maximum performance over all 2000 simulations is reported in table 2.

As shown in Figure 3, the DAPSKV outperformed the other fingerprints using the KNN classifier. Its maximum correct identification percentage was 80% when k=3. It was followed by the fractal dimension fingerprint with maximum correct identification percentage of 79% when k=6, 8, and 11. The intrinsic shape and polynomial fit fingerprints had maximum correct identification percentages of 71% and 60%, respectively. It should be noted that these maximums occurred at different k-neighbour values. In general, the correct identification percentage decreases as k increases. KNN is simple for implementation; however, one must determine an ideal k value.

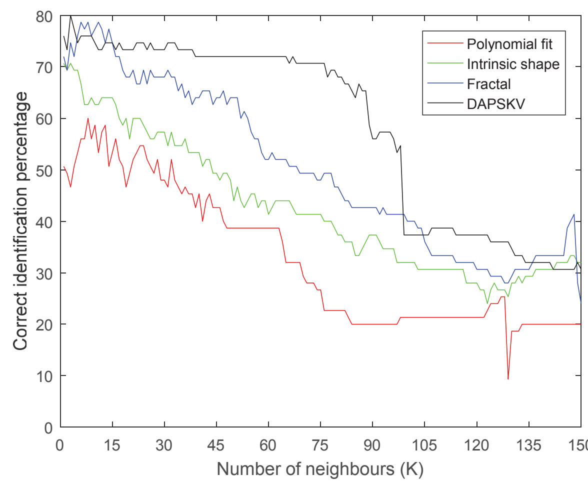

Figure 3. Emitter identification performance using KNN classification on one of the 2000 simulations.

The correct identification percentages of the natural measure fingerprint were generated by randomly choosing three testing pulses from the same emitter and finding their PMF's relative entropy with each PMFT.

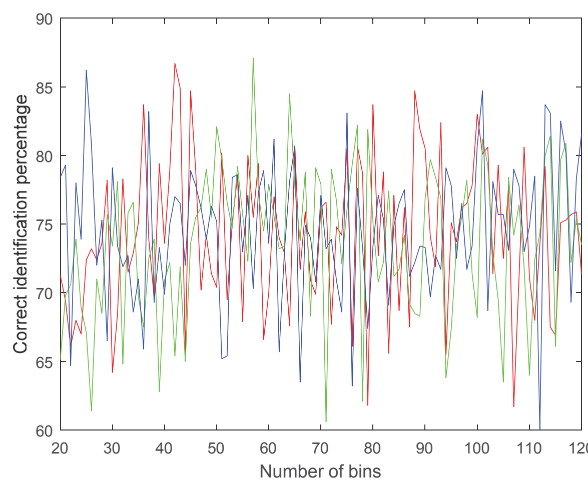

Figure 4. Emitter identification performance using D_{KLD} for three of the simulations (in red, blue, green).

For the relative entropy classifier, the number of bins used to create the PMFs was altered. The correct identification percentage as a function of the number of bins is shown in Figure 4 for three Monte Carlo simulations. It was observed that the maximums occurred at different bin sizes (i.e., 25 bins for blue, 42 for red, and 57 for green). On average, this method achieves a maximum correct identification percentage of 86% over the 2000 simulations as reported in Table 2. The number of bins varies from 20 to 120. A drawback of D_{KLD} is that one must determine an ideal bin number. However, it is robust in that it compares the entire distribution of energy between transients instead of summarizing them into one statistical or physical vector.

For the QDA classifier, a multivariate normal distribution was fitted onto the training data, the probability that each testing fingerprint came from each emitter was calculated using Equation (18), and the pulse was classified according to the maximum probability. This strict assumption of normality is a drawback of QDA. It is advantageous as it does not rely on any sort of tuning parameters, such as *k* in KNN. The summary of QDA results is in table 2.

Table 2 provides a performance summary of all five RF fingerprints with KNN, QDA, and D_{KLD} classifiers. Each cell value is the mean of the maximum (over tuning parameters *k* and bin number) correct identification percentages or simply the mean for QDA over 2000 Monte Carlo runs.

Natural measure achieves a mean correct identification percentage of 86%. DAPSKV and Intrinsic Shape achieve a mean correct identification percentage of 84% and 82%, respectively.

Table 2 also shows that the QDA outperformed KNN for all of the fingerprints. It was observed that the DAPSKV performed the best with the QDA classification system.

Table 2. Summary of emitter identification performance.

fingerprints / classifier	Intrinsic Shape	Fractal dimension	Polynomial Coefficients	DAPSKV	Natural measure
KNN	0.73	0.75	0.60	0.80	
QDA	**0.82**	**0.76**	**0.70**	**0.84**	
D_{KLD}					**0.86**

V. CONCLUSIONS

The intrinsic shape fingerprint was proposed in this paper. The performance of five radar emitter identification methods (incl. intrinsic shape) were tested and compared. These SEI methods only use the signal transient of a pulse, without making use of any classical pulse parameters, to identify radar emitters.

Our results show that the natural measures, DAPSKV, and the intrinsic shape achieve very competitive emitter identification performances of about 86%, 84% and 82%, respectively, using the selected radar datasets and classification algorithms. This study also demonstrates that a careful selection of a combination of RF fingerprints and classification methods is required for radar emitter identification. The performance of an RF fingerprint will be different under different classification systems.

The radar signal dataset that was used does not contain emissions from different instances of the same radar model. However, the techniques investigated here all expose interesting properties about radar signals for radar SEI. Future research will focus on: (1) evaluating these techniques using a dataset that contains emissions from many different instances of the same radar model, (2) finding new classification methods (i.e., neural network, decision trees etc.) and new statistical and physical parameters for quantifying unique shapes and features of the normalized transients, (3) create new fingerprint using feature selection algorithms on all features, and (4) compare energy trajectory with moving average on signal amplitudes.

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Radar emitter identification has been studied for decades using library-based techniques that rely on pre-existing knowledge of parameters such as radio frequency (RF), pulse amplitude, pulse width, intentional pulse modulation type, or pulse repetition intervals. However, current radar emitter identification techniques will not be sufficient against cognitive radars due to their parameter agility and adaptability. In this study, five radar emitter identification fingerprints based on radar signal transients were analyzed and compared. These fingerprints include: (1) fractal dimension estimation of signal transients, (2) natural measures of signal transients, (3) polynomial regression of a signal transient energy trajectory acquired by its 4th order cumulants, (4) RF fingerprints based on the energy trajectory characteristics of signal transients, and (5) intrinsic shape of the rising edge of a pulse. The analysis and comparison were performed using K-Nearest Neighbours, Quadratic Discriminant Analysis, and relative entropy over a dataset from five different radar emitters. The advantages and drawbacks of each technique are highlighted. Our results show that (2), (4) and (5) achieve very competitive emitter identification performance using the selected radar datasets and classification algorithms. This study also demonstrates that the optimal emitter identification performance is dependent on the combination of RF fingerprints and classification algorithms.

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Radar emitter identification, Radar SEI, Entropy, Fractal, Machine learning