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Specific Emitter Identification Based on Refined Composite Multiscale Dispersion Entropy

Shaoying Guo, Yanyun Xu, Meng Zhang, Weiqing Huang

***Abstract*—The wireless communication network is developing rapidly, thus the wireless security becomes more and more important. Specific emitter identification(SEI) is an vital part of wireless communication security as a technique to identify the unique transmitters. In this paper, a SEI method based on multiscale dispersion entropy(MDE) and refined composite multiscale dispersion entropy(RCMDE) is proposed. The algorithms of MDE and RCMDE are used to extract features for identification of five wireless devices and cross-validation support vector machine (CV-SVM) is used as the classifier. The experimental results show that the total identification accuracy is 99.3%, even at low signal-to-noise ratio(SNR) of 5dB, which proves that MDE and RCMDE can describe the communication signal series well. In addition, compared with other methods, the proposed method is effective and provides better accuracy and stability for SEI.

***Keywords*—Cross-validation support vector machine, refined composite multiscale dispersion entropy, specific emitter identification, transient signal, wireless communication device.

I. INTRODUCTION

WITH the development of the wireless communication network, the wireless networks face with serious security threats. The wireless communication security becomes more and more important and has attracted much attention in recent years.

Specific emitter identification (SEI) is a technique to identify the unique RF transmitters and has been applied to enhance the wireless communication security. SEI technique associates a given signal with a unique emitter by comparing the subtle features of the given signal with a library of feature sets that uniquely identify a signal and selecting the class that best matches [1]. The key of SEI is extracting radio frequency(RF) fingerprint because of its uniqueness which is similar to human fingerprints. RF fingerprint represents the inconsistency in the production process of the wireless emitters components including printed circuit boards, power amplifiers and other components [2].

In the case of communication signals, SEI techniques are generally classified into two categories: transient based and steady-state based [3]. A transient signal is the part that the output power of the transmitter goes from zero to the level needed for communications. A steady state signal is the part between the transient signal and the end of the whole pulse signal. Transient based SEI techniques were firstly proposed in the 1990s [4], [5], then scholars and research institutions investigated the feature extraction methods based on transient signals for a little over a decade. The steady-state based techniques were firstly proposed until 2008 [3].

Much research has been done based on transient signals. The statistical features including variance, skewness, kurtosis and others were used as RF fingerprint in [6], [7]. The high order statistics of the transients envelope were also extracted as features for classification. The Short Time Fourier Transform(STFT) was utilized to obtain the energy envelope of the instantaneous transient signal and six features were extracted from the envelope such as kurtosis, skewness, variance, maximum slope [8].

There are also a great number of studies based on steady state signals. The preamble of a whole signal was extracted and then RF fingerprint was extracted from the preamble sequences [3], [9], [10]. In [11]–[13], the RF feature extraction was based on modulation characteristics, such as frequency difference, I/Q origin offset, constellation errors and so on. The wavelet-based technique was utilized to extract features for SEI [14] [15]. The authors in [16] extracted the fingerprint features from integral bispectrum. In [17], the fractal dimensions were used to extract the fingerprint features.

In addition to the transient based and steady-state based techniques, there are other RF fingerprint methods which are analyzed from another aspect, such as nonlinear techniques.

It is considered that the actual communication signals contain nonlinear property. Carroll has demonstrated that amplifiers of transmitters contain unavoidable nonlinearities because they depend on semiconductors [18]. As a result, the nonlinear characteristics of communication transmitters signals can be extracted as the RF fingerprints.

As a nonlinear dynamic parameter, entropy is an effective and broadly used measure of the irregularity and uncertainty of time series [19], [20]. In recent years, Xie et al. firstly developed an improved Approximate Entropy (imApEn) algorithm to extract the nonlinear complexity of the signals as a new RF fingerprint [21]. Permutation entropy has also been applied to identify the unique transmitter [22]–[24]. The researchers have also used dispersion entropy (DisEn), which has never been used previously for RF fingerprint [22].

The multiscale dispersion entropy(MDE) is a fast and powerful technique to quantify the complexity of signals, and it has been used for the analysis of physiological signals thanks

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to their ability to distinguish different types of dynamics [25], [26]. The authors in [26] also proposed refined composite multiscale dispersion entropy (RCMDE) for improving the stability of MDE by extracting the complexity features across multiple time scales. These entropy-based methods can obtain stable results for noisy signals thanks to the coarse-graining process.

In this paper, a novel SEI method based on multiscale dispersion entropy (MDE) and refined composite multiscale dispersion entropy(RCMDE) is proposed. The method includes a complete identification process and the performance of the method is confirmed by experimental results. In addition, the proposed method is compared with some aforementioned SEI methods using the same communication signals.

The rest of the paper is organized as follows. In Section II, the definition of MDE and RCMDE are introduced. In Section III, the proposed SEI method is explained in detail. In Section IV, the experimental results are provided and the comparison with different statistical features is analyzed. Finally Section V concludes the paper.

II. Definition of MDE and RCMDE

A. Multiscale Dispersion Entropy (MDE)

The algorithm of MDE includes two main steps [26], as shown in Fig. 1. Firstly, the original signal $\mathrm{u} = \{u_1, u_2, \ldots, u_L\}$ is divided into several non-overlapping segments of length τ. The parameter τ is called scale factor. The coarse-grained [27] signals can be derived by calculating the average of each segment as follows:

$$x_j^{(\tau)} = \frac{1}{\tau} \sum_{b=(j-1)\tau+1}^{j\tau} u_b, \quad 1 \le j \le \left\lfloor \frac{L}{\tau} \right\rfloor = N \qquad (1)$$

The second step is calculating the entropy value for each coarse-grained signal using DisEn. It is worth noting that MDE is more than the combination of the coarse-graining [27] with DisEn.

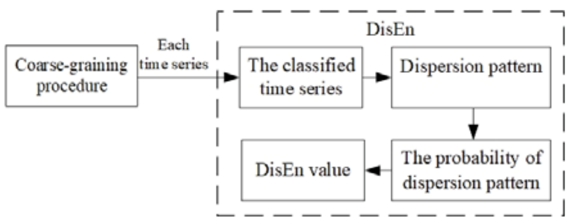


Fig. 1 The MDE algorithm

The definition of the DisEn for series $\mathrm{x} = \{x_1, x_2, \ldots, x_\mathrm{N}\}$ is introduced as follows:

1) Obtaining the Classified Time Series: The series $\mathrm{x} = \{x_1, x_2, \ldots, x_\mathrm{N}\}$ obtained from the first step is mapped into $\mathrm{y} = \{y_1, y_2, \ldots, y_\mathrm{N}\}$ from 0 to 1 using the normal cumulative distribution function (NCDF) as follows:

$$y_j = \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{x_j} e^{\frac{-(t-\mu)^2}{2\sigma^2}} dt \qquad (2)$$

where μ and σ are the mean and standard deviation (SD) of time series x, respectively. Both of the parameters are constant for all scale factor τ. Then each y_j is mapped to an integer from 1 to c using the linear algorithm $z_j^c = round\left(c \cdot y_j + 0.5\right)$.

2) Generating the Dispersion Pattern: The series $z_i^{m,c}$ are generated as follow [19], [20], [28]:

$$z_i^{m,c} = \left\{ z_i^c, z_{i+d}^c, \ldots, z_{i+(m-1)d}^c \right\}, i = 1, 2, \ldots, N-(m-1)d \qquad (3)$$

where m is the embedding dimension and d is the time delay. Each series $z_i^{m,c}$ is mapped to a dispersion pattern $\pi_{v_0 v_1 \ldots v_{m-1}}$, where $z_i^c = v_0, z_{i+d}^c = v_1, \ldots, z_{i+(m-1)d}^c = v_{m-1}$.

3) Calculating the Probability: The probability for each potential dispersion pattern $\pi_{v_0 \ldots v_{m-1}}$ is obtained as follows:

$$p\left(\pi_{v_0 \ldots v_{m-1}}\right) = \frac{number\{i | i \le N-(m-1)d, z_i^{m,c} has\ type\ \pi_{v_0 \ldots v_{m-1}}\}}{N-(m-1)d} \qquad (4)$$

4) Calculating the DisEn Value: The DisEn value is obtained as follows:

$$DisEn(\mathrm{x}, m, c, d) = -\sum_{\pi=1}^{c^m} p\left(\pi_{v_0 \ldots v_{m-1}}\right) \cdot \ln\left(p\left(\pi_{v_0 \ldots v_{m-1}}\right)\right) \qquad (5)$$

B. Refined Composite Multiscale Dispersion Entropy (RCMDE)

The RCMDE algorithm is similar to MDE, but there is something different in the first step. A modified coarse graining procedure is used to drive the coarse-grained series. The k^{th} coarse-grained time series $\mathbf{X}_k^{(\tau)}$ of the original signal u is derived as follows:

$$x_{k,j}^{(\tau)} = \frac{1}{\tau} \sum_{b=k+\tau(j-1)}^{k+y-1} u_b, \quad 1 \le j \le N, \quad 1 \le k \le \tau \qquad (6)$$

For different scale factor τ, the starting points of the coarse-grained process are different. Then, the DisEn is used to calculate the relative frequency of each potential dispersion pattern. Finally, for each scale factor τ, RCMDE is obtained as follows:

$$RCMDE(\mathrm{x},m,c,d,\tau) = -\sum_{\pi=1}^{c^m} \overline{p}\left(\pi_{v_0 \ldots v_{m-1}}\right) \cdot \ln\left(\overline{p}\left(\pi_{v_0, v_{m-1}}\right)\right) \qquad (7)$$

where $\overline{p}\left(\pi_{v_0 \ldots v_{m-1}}\right) = \frac{1}{\tau}\sum_1^t p_k^{(\tau)}$ is the relative frequency of the dispersion pattern π in the series $\mathrm{x}_k^{(\tau)} (1 \le k \le \tau)$.

III. The Proposed Method

The method for SEI proposed in this paper is presented in this section. The flowchart of the complete SEI method is shown in Fig. 2.

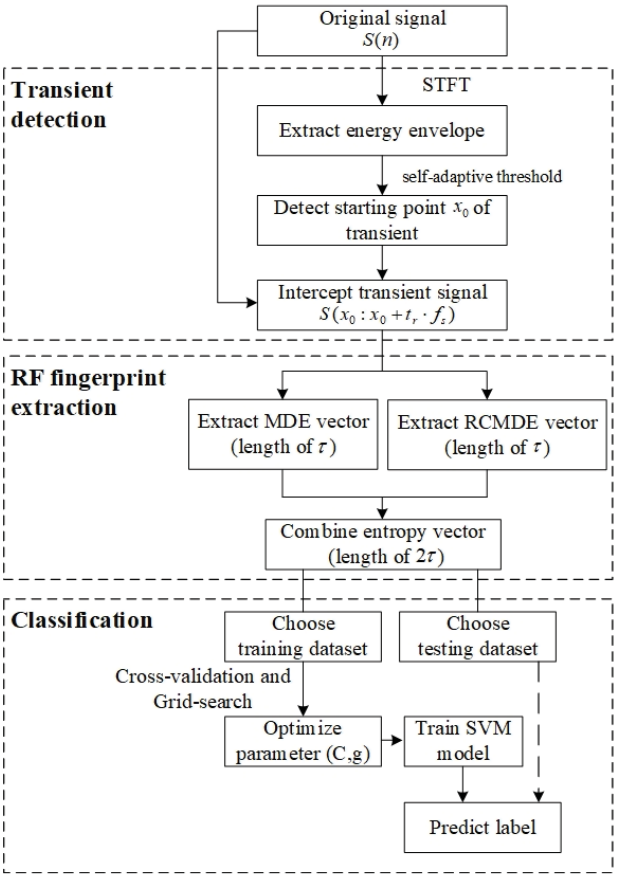
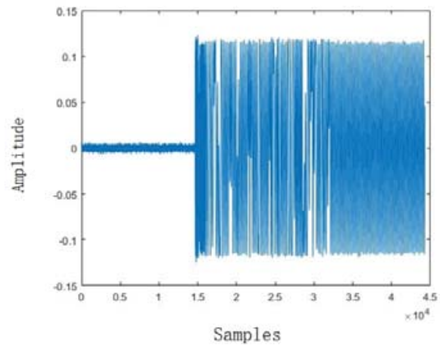
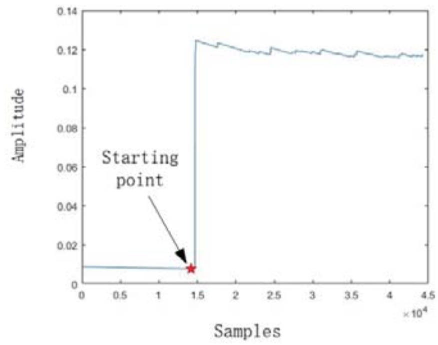


Fig. 2 The proposed SEI method



(a) The former part of a burst



(b) The energy envelope

Fig. 3 Transient detection

A. Transient Detection

It has been known that the transient signals from different emitters usually have special RF fingerprint for SEI. Therefore, transient signals are chosen to extract features and transient extraction plays an important role in the complete SEI process. As illustrated in Fig. 3 (a), the former part of a burst contains channel noises, power ramp-up transient signal and stable signal. If a transient is not extracted properly, the features extracted from the transient signal will carry information from channel noise or the steady state part of the signal.

In order to extract the transients automatically, a self-adaptive threshold method based on envelope is used. Firstly, the energy envelope of the collected signal is obtained using the Short Time Fourier Transform (STFT) [8]. Then smoothing the envelope with a low-pass filter is performed in order to find the start point easier. The envelope value is obviously different between channel noise and transient signal as shown in Fig. 3 (b).

The start point is defined as the point that all the values in the envelope after it are bigger than the threshold. The threshold is defined as follows:

$$threshold = \alpha \cdot (value\_Max - value\_Min) \quad (8)$$

where $value\_Max$ is the maximum value of the envelope and $value\_Min$ is the minimum value. The parameter α is set to 2/3 based on experiments.

After finding the starting point, the transient data is extracted with a fixed length from the start point. According to the sampling rate f_s and the power rising time t_r, the length of the transient is set as $t_r \cdot f_s$.

B. RF Fingerprint Extraction

Two feature vectors is extracted from the transients using the MDE and RCMDE algorithms, respectively, which are described in Section II. These two vectors are combined together into one entropy vector as the RF fingerprint.

Choosing appropriate parameter values is important for every entropy-based approach. There are four parameters for MDE and RCMDE, including the number of classes c, the embedding dimension m, the time delay d, and the maximum scale factor τ. No detailed analysis is made for parameter selection in this paper. Nevertheless, it is mentioned that the range $2 < c < 9$ leads to similar results in [20].

Therefore, the parameters are set as $c = 6$, $m = 2$, $d = 1$ according to [20]. In addition, the scale factor τ is assigned equal to 10 which means the length of the entropy values is 10 for MDE or RCMDE. And all the entropy values are chosen as the features for each transient.

C. Classification

Cross-validation support vector machine (CV-SVM) [29] is used to classify the feature vectors. Traditional SVM chooses parameters from experience. However, CV-SVM can obtain the optimum parameters.

The support vector machine(SVM) theory is a state-of-the art supervised machine learning algorithm proposed to solve the pattern recognition problem. SVM can solve linearly inseparable problems efficiently by mapping a linearly inseparable space to a linearly separable high-dimensional feature space and a linear separator can be found in it.

In the high-dimensional feature space, it is able to find a separating hyperplane with the largest margin and the hyperplane can maximize the space between different classes [30]. For the linearly inseparable data, the classification function is defined as:

$$f(x) = sign\left[\left(\sum_{i=1}^{L} \alpha_i y_i K\left(x_i, x_j\right)\right) + b\right] \tag{9}$$

where $K\left(x_i, x_j\right)$ is the kernel function.

Based on the basic model, the idea of cross-validation and grid-search [31] is used to optimize the parameters of the SVM model. The parameters C and g are the penalty parameter of the error term and kernel parameter, respectively. It can be seen that when (C, g) takes different values, the classification accuracy is different. Cross-validation aims at finding the parameter pairs (C, g) with the highest cross-validation accuracy by trying various combinations of parameters C and g.

A model can be generated with the best parameters from the training dataset. The testing dataset is classified with the model. The identification accuracy is defined as follows:

$$Accuracy = \frac{number\{correctly\ classified\ samples\}}{number\{all\ testing\ samples\}} \tag{10}$$

IV. Experiment and Result Analysis

A. Experiment

In out experiment, five nRF24L01 wireless devices are used and they are marked as D1 to D5, respectively. The five transmitters are configured to transmit a fixed payload with a data rate of 1Mbit/sec, and to operate in the following frequency band :2510-2530MHz with the center frequency 2520MHz.

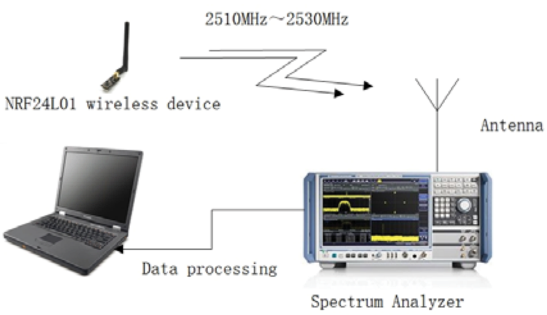


Fig. 4 Signal acquisition system

The signal acquisition system is used to collect RF signals from the transmitters, as shown in Fig. 4.

A ROHDE&SCHWARZ FSW13 signal and spectrum analyzer connected to a antenna converts the RF signals to the baseband. The frequency center and the measurement bandwidth are set as 2520 MHz and 20MHz, respectively. A computer controls the signal and spectrum analyzer via local area network and the signal samples are sampled directly in In-phase and Quadrature components (IQ) format at a sampling rate of 40Msps. For each wireless device, a set of 160 packets are collected.

For the collected signals, the transient detection and RF features extraction are operated as the process in Fig. 2. At the classification stage, the features of all transients are divided into two parts: the training dataset and the test dataset. For each emitter, the training set has 100 samples and the test set has 60 samples.

To verify the performance of the proposed SEI method at different signal-to-noise ratios(SNRs), gaussian white noise is added to the signals of D1-D5. The SNR is set from -5dB to 30dB at intervals of 5dB.

B. Result Analysis

Three of 20 entropy values of MDE and RCMDE are chosen to generated a three-dimensional scatter diagram as Fig. 5(SNR=5dB). In this figure, the 1st eigenvalue is on the x axis and the 10th eigenvalue is on the y axis with the 2nd eigenvalue on the z axis. The points of the same shape are from the same emitter and each point corresponds to one transient. It is obvious in Fig. 5 that the points of the same emitter are clustered into one cluster and there is little overlap between different clusters. It means that these eigenvalues are able to separate various emitters. In other words, the method based on MDE and RCMDE is suitable for classification.

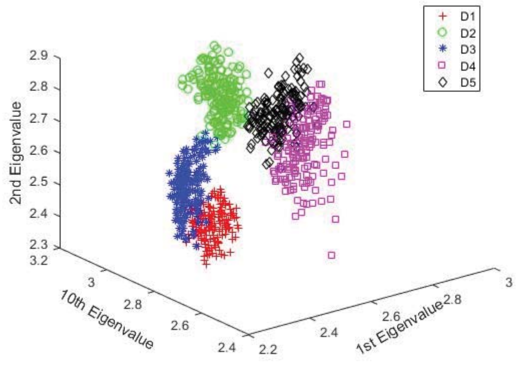


Fig. 5 Scatter diagram with 1st eigenvalue, 2nd eigenvalue and 10th eigenvalue for D1-D5

The performance of MDE and RCMDE is demonstrated under different SNRs situations in order to evaluate the anti-noise capability and stability. As shown in Table I, it can be seen that the recognition rate of the proposed method remains high under different SNR conditions. The recognition rate can reach 99.3% even at the SNR of 5dB.

In order to verify the effectiveness of the proposed method, a comparative experiment is also operated. Other features are

TABLE I
THE RECOGNITION RATES (%)

Method	SNR							
	-5dB	0dB	5dB	10dB	15dB	20dB	25dB	30dB
variance+kurtosis+skewness+shannon entropy	44	64.8	72	72	67.67	74.33	69.33	70.67
J-R(high order statistics)	22.86	28	35.33	45.33	52	51.67	56.33	58.67
variance+kurtosis+skewness+shannon entropy+J-R	40.57	68.8	68	76.4	80.67	83.33	84.33	85.33
DE	21.71	34	39.67	49.33	56	51.33	53.67	45.67
MDE+RCMDE	**85.71**	**99**	**99.33**	**98.67**	**99**	**97.67**	**98.33**	**99**

extracted as a contrast including variance, kurtosis, skewness, Shannon entropy and high order statistics of the transients envelope. The combinations of features has been set up to evaluate the performance better, as shown in Table I.

The corresponding results are shown in Table I and a line chart is created as Fig. 6.

Fig. 6 shows the change of the total accuracy using different features sets with the SNR from -5dB to 30dB. It can be seen that the accuracy of MDE and RCMDE is higher than others clearly when the SNR is above -5dB. Furthermore, the recognition rates keep steady with the SNR varying from 0dB to 30 dB when the MDE and RCMDE is applied.

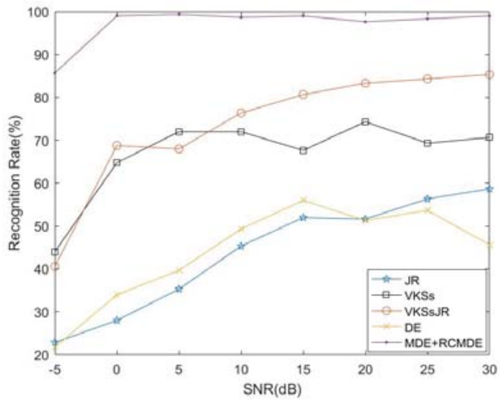


Fig. 6 Recognition rates with different SNRs

It is obvious that the proposed method based on MDE and RCMDE has higher recognition rate than other features such as variance, kurtosis, skewness, Shannon entropy and high order statistics J-R of the envelope . The accuracy of proposed method based on MDE and RCMDE is above 97% with the SNR from 0dB to 30dB. And the accuracy can reach 85% even the SNR is -5dB.

Aiming at proving the robustness and stability of the proposed method, 100 repetitive experiments using the proposed method(SNR=5dB) are also carried out in our experiment. For each emitter, 100 features vectors are chosen randomly to create a training set and the rest 60 feature vectors are used as a test set. The total recognition rate and the rates of emitters D1-D5 are obtained in each experiment. A boxplot of 100 experiments results is generated as shown in Fig. 7.

It can be seen that the median value of the total recognition rate is 98.83% and the smallest value is 98% without considering the outliers. And the median value of the recognition rate for D1-D3 is 100% with the smallest value greater than 96%. The rates of D4 and D5 are all above 95% for all experiments. Overall, the recognition performance

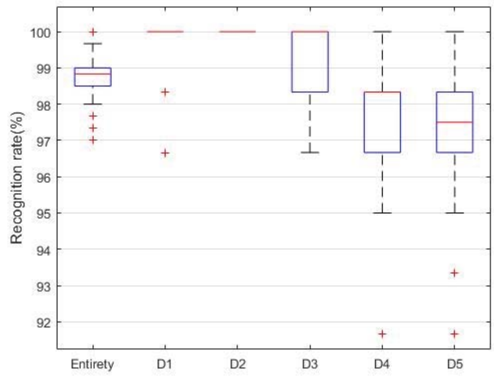


Fig. 7 Boxplot for 100 experiments

keeps high steadily according to the results, which means that the SEI method proposed in this paper is suitable for wireless devices classification.

V. CONCLUSION

This paper proposes a SEI method based on MDE and RCMDE considering the inherent nonlinearities of the wireless devices. The entropy values of MDE and RCMDE are extracted as feature vectors, which can describe the inherent nonlinear dynamical characteristics. CV-SVM is used as a classifier and a series of experiments are performed to evaluate the proposed method with five NRF24L01 devices. The classification experimental results demonstrate that the proposed method is effective and can achieve a good performance even at a low SNR. In the future work, other noises except gaussian white noise will be taken into consideration and the performance of the proposed method can be verified further using other wireless devices such as Bluetooth devices. In addition, increasing the number of wireless devices for classification will be also considered.

REFERENCES

[1] K. I. Talbot, P. R. Duley, and M. H. Hyatt, “Specific emitter identification and verification,” *Technology Review*, vol. 113, 2003.

[2] Z. Li, Y. Yin, and L. Wu, “Radio frequency fingerprint identification method in wireless communication,” in *International Conference on Machine Learning and Intelligent Communications*. Springer, 2017, pp. 195–202.

[3] I. O. Kennedy, P. Scanlon, F. J. Mullany, M. M. Buddhikot, K. E. Nolan, and T. W. Rondeau, “Radio transmitter fingerprinting: A steady state frequency domain approach,” in *2008 IEEE 68th Vehicular Technology Conference*. IEEE, 2008, pp. 1–5.

[4] H. C. Choe, C. E. Poole, M. Y. Andrea, and H. H. Szu, "Novel identification of intercepted signals from unknown radio transmitters," in *Wavelet Applications II*, vol. 2491. International Society for Optics and Photonics, 1995, pp. 504–518.

[5] J. Toonstra and W. Kinsner, "Transient analysis and genetic algorithms for classification," in *IEEE WESCANEX 95. Communications, Power, and Computing. Conference Proceedings*, vol. 2. IEEE, 1995, pp. 432–437.

[6] R. Klein, M. A. Temple, M. J. Mendenhall, and D. R. Reising, "Sensitivity analysis of burst detection and rf fingerprinting classification performance," in *2009 IEEE International Conference on Communications*. IEEE, 2009, pp. 1–5.

[7] W. C. Suski II, M. A. Temple, M. J. Mendenhall, and R. F. Mills, "Using spectral fingerprints to improve wireless network security," in *IEEE GLOBECOM 2008-2008 IEEE Global Telecommunications Conference*. IEEE, 2008, pp. 1–5.

[8] S. U. Rehman, K. Sowerby, and C. Coghill, "Rf fingerprint extraction from the energy envelope of an instantaneous transient signal," in *2012 Australian Communications Theory Workshop (AusCTW)*. IEEE, 2012, pp. 90–95.

[9] H. Yuan and A. Hu, "Preamble-based detection of wi-fi transmitter rf fingerprints," *Electronics letters*, vol. 46, no. 16, pp. 1165–1167, 2010.

[10] P. Padilla, J. Padilla, and J. Valenzuela-Valdes, "Radio frequency identification of wireless devices based on rf fingerprinting," *Electronics Letters*, vol. 49, no. 22, pp. 1409–1410, 2013.

[11] A. Candore, O. Kocabas, and F. Koushanfar, "Robust stable radiometric fingerprinting for wireless devices," in *2009 IEEE International Workshop on Hardware-Oriented Security and Trust*. IEEE, 2009, pp. 43–49.

[12] Y. Huang and H. Zheng, "Radio frequency fingerprinting based on the constellation errors," in *2012 18th Asia-Pacific Conference on Communications (APCC)*. IEEE, 2012, pp. 900–905.

[13] V. Brik, S. Banerjee, M. Gruteser, and S. Oh, "Wireless device identification with radiometric signatures," in *Proceedings of the 14th ACM international conference on Mobile computing and networking*. ACM, 2008, pp. 116–127.

[14] R. W. Klein, M. A. Temple, and M. J. Mendenhall, "Application of wavelet-based rf fingerprinting to enhance wireless network security," *Journal of Communications and Networks*, vol. 11, no. 6, pp. 544–555, 2009.

[15] C. Bertoncini, K. Rudd, B. Nousain, and M. Hinders, "Wavelet fingerprinting of radio-frequency identification (rfid) tags," *IEEE Transactions on Industrial Electronics*, vol. 59, no. 12, pp. 4843–4850, 2012.

[16] L. Xuan-min, Y. Ju, and Z. Ya-jian, "A new method based on local integral bispectra and svm for radio transmitter individual identification," in *2010 WASE international conference on information engineering*, vol. 4. IEEE, 2010, pp. 65–68.

[17] S. Xu, L. Xu, Z. Xu, and B. Huang, "Individual radio transmitter identification based on spurious modulation characteristics of signal envelop," in *MILCOM 2008-2008 IEEE Military Communications Conference*. IEEE, 2008, pp. 1–5.

[18] T. Carroll, "A nonlinear dynamics method for signal identification," *Chaos: An Interdisciplinary Journal of Nonlinear Science*, vol. 17, no. 2, p. 023109, 2007.

[19] J. S. Richman and J. R. Moorman, "Physiological time-series analysis using approximate entropy and sample entropy," *American Journal of Physiology-Heart and Circulatory Physiology*, vol. 278, no. 6, pp. H2039–H2049, 2000.

[20] M. Rostaghi and H. Azami, "Dispersion entropy: A measure for time-series analysis," *IEEE Signal Processing Letters*, vol. 23, no. 5, pp. 610–614, 2016.

[21] Y. Xie, S. Wang, E. Zhang, and Z. Zhao, "Specific emitter identification based on nonlinear complexity of signal," in *2016 IEEE International Conference on Signal Processing, Communications and Computing (ICSPCC)*. IEEE, 2016, pp. 1–6.

[22] G. Baldini, R. Giuliani, G. Steri, and R. Neisse, "Physical layer authentication of internet of things wireless devices through permutation and dispersion entropy," in *2017 Global Internet of Things Summit (GIoTS)*. IEEE, 2017, pp. 1–6.

[23] S. Deng, Z. Huang, X. Wang, and G. Huang, "Radio frequency fingerprint extraction based on multidimension permutation entropy," *International Journal of Antennas and Propagation*, vol. 2017, 2017.

[24] G. Huang, Y. Yuan, X. Wang, and Z. Huang, "Specific emitter identification based on nonlinear dynamical characteristics," *Canadian Journal of Electrical and Computer Engineering*, vol. 39, no. 1, pp. 34–41, 2016.

[25] H. Azami, E. Kinney-Lang, A. Ebied, A. Fernández, and J. Escudero, "Multiscale dispersion entropy for the regional analysis of resting-state magnetoencephalogram complexity in alzheimer's disease," in *2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2017, pp. 3182–3185.

[26] H. Azami, M. Rostaghi, D. Abásolo, and J. Escudero, "Refined composite multiscale dispersion entropy and its application to biomedical signals," *IEEE Transactions on Biomedical Engineering*, vol. 64, no. 12, pp. 2872–2879, 2017.

[27] M. Costa, A. L. Goldberger, and C.-K. Peng, "Multiscale entropy analysis of biological signals," *Physical review E*, vol. 71, no. 2, p. 021906, 2005.

[28] C. Bandt and B. Pompe, "Permutation entropy: a natural complexity measure for time series," *Physical review letters*, vol. 88, no. 17, p. 174102, 2002.

[29] Z. Zhang, X. Guo, and Y. Lin, "Trust management method of d2d communication based on rf fingerprint identification," *IEEE Access*, vol. 6, pp. 66 082–66 087, 2018.

[30] C. J. Burges, "A tutorial on support vector machine for pattern recognition," *Data mining and knowledge discovery*, vol. 2, no. 2, pp. 955–974, 1998.

[31] C.-W. Hsu, C.-C. Chang, C.-J. Lin *et al.*, "A practical guide to support vector classification," 2003.