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Behavior Modeling and Individual Recognition of Sonar Transmitter for Secure Communication in UASNs

FAN SHI[1], ZHENLEI CHEN[1], AND XIAOCHUN CHENG[2], (Senior Member, IEEE)
[1]Faculty of Maritime and Transportation, Ningbo University, Ningbo 315211, China
[2]Department of Computer Science, Middlesex University, London NW4 4BT, U.K.

Corresponding author: Zhenlei Chen (artchenzhenlei@126.com)

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ABSTRACT It is necessary to improve the safety of the underwater acoustic sensor networks (UASNs) since it is mostly used in the military industry. Specific emitter identification is the process of identifying different transmitters based on the radio frequency fingerprint extracted from the received signal. The sonar transmitter is a typical low-frequency radiation source and is an important part of the UASNs. Class D power amplifier, a typical nonlinear amplifier, is usually used in sonar transmitters. The inherent nonlinearity of power amplifiers provides fingerprint features that can be distinguished without transmitters for specific emitter recognition. First, the nonlinearity of the sonar transmitter is studied in-depth, and the nonlinearity of the power amplifier is modeled and its nonlinearity characteristics are analyzed. After obtaining the nonlinear model of an amplifier, a similar amplifier in practical application is obtained by changing its model parameters as the research object. The output signals are collected by giving the same input of different models, and, then, the output signals are extracted and classified. In this paper, the memory polynomial model is used to model the amplifier. The power spectrum features of the output signals are extracted as fingerprint features. Then, the dimensionality of the high-dimensional features is reduced. Finally, the classifier is used to recognize the amplifier. The experimental results show that the individual sonar transmitter can be well identified by using the nonlinear characteristics of the signal. By this way, this method can enhance the communication safety of the UASNs.

INDEX TERMS Specific emitter identification, sonar, nonlinear model, power amplifier.

I. INTRODUCTION

The ubderwater acoustic sensor networks (UASNs) are often used for environmental and industrial sensing in undersea space or space. Therefore, these networks are also named underwater sensor networks(UWSNs). Underwater sensor networks are different from other sensor networks [1], [2]. Monitoring of underwater environment is very important in marine science and technology. To cover this monitoring, creating underwater sensor networks is essential in undersea space.

The sound of water is the only form of energy that humans have known so far that can travel long distances in the ocean. Other physical media, such as visible light, electromagnetic waves, lasers, etc., will quickly decay when propagating in seawater and cannot be transmitted to distant places. Therefore, sonar technology is an important means of acquiring, utilizing and processing marine information, and has a unique role in national security and national economic development. The invention of modern sonar is earlier than radar, but the public's understanding of sonar is far less than that of radar. This is because the sonar is mainly used for the detection of surface ships and submarines in the military, and the modern is extended to the underwater warning, anti-frogmen, etc. So the sonar is covered with a mysterious veil. In the civilian sector, sonar technology is an important means of understanding various parameters of the sea surface, water body and seabed, including sound velocity profile, temperature, and salt depth distribution, ocean current, internal wave, mesoscale vortex, seabed landform/topography, etc. Sonar equipment is also used in submarine scientific observation networks, submarine oil and gas field exploration,

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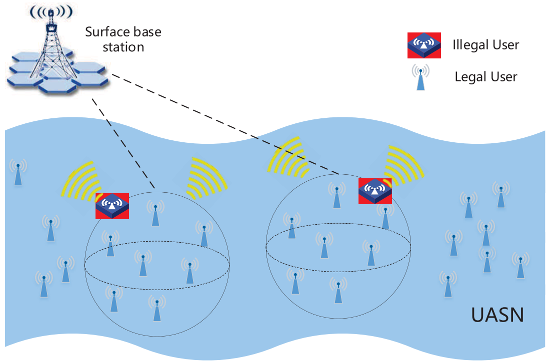


FIGURE 1. The power spectrum estimation of the output signals of linear and nonlinear systems.

shipwreck rescue, underwater testing, ancient and marine disaster warnings [3], [4]. In the field of national security, sonar equipment is installed on a variety of platforms, including surface ships, submarines, helicopters, unmanned/manned submersibles, shore stations, torpedoes, mines, etc., for information collection, remote warning, targeting and Identification, navigation, proximity/long-range weapon guidance, etc. Figure 1 shows a basic UASNs. There are many known or unknown sonar transmitters underwater. Each transmitter emits a different signal. If each transmitter cannot be identified, it poses a threat to the secure communication of the network.

Individual identification of specific emitter is a technology to extract the fingerprint characteristics of communication equipment by analyzing the radio frequency signal of communication equipment, and then identify the individual of communication equipment [5], [6]. It is also an important non-cryptographic authentication method based on physical layer hardware of equipment. Currently, the research object of individual identification of specific emitters is mainly radar and communication radio [7], [8]. The working frequency is generally radio frequency, and the working frequency will reach MHz or even GHz. For example, individual identification based on RFID and individual identification based on wireless network card or ZigBee device, their working frequency has reached 2.4 GHz [9], [10].

Individual identification of low-frequency emitters is also a very important subject in the field of communication and electronic countermeasures. The sonar transmitter studied in this paper is a typical low-frequency radiation source. Its working frequency is usually from several hundred Hz to several hundred KHz. Although the working frequency bands are different, the idea of individual identification of radiation sources is similar. With the rapid development of modern military, modern underwater warfare has become a key part. Underwater vehicle must rely on underwater acoustic countermeasure to grasp underwater information in order to ensure underwater activities.

With the development of modern underwater acoustic countermeasure, it is necessary to have good sonar equipment in order to grasp the direction of enemy submarines. So sonar equipment plays an important role in underwater, so there will be many sonar equipment. At this time, new problems will arise. Such as how to distinguish the cooperative sonar equipment accurately, avoid the deceptive operation of the enemy sonar equipment and so on. Therefore, it is of great significance to study the individual recognition technology of sonar transmitter.

Like different individual fingerprints, each sonar device will have subtle differences in design, production, processing and modulation. This hardware difference will be reflected in the sonar transmission signal. By analyzing the received sonar signal, this subtle difference can be extracted, and then used for sonar transmitter individual identification. In 2003, Hall et al. of Canada first proposed in document [11] to extract the subtle differences in Bluetooth signals for individual identification of Bluetooth devices, and defined these subtle features as "radio frequency fingerprints" [11]. Radio frequency fingerprint extraction and recognition of wireless communication equipment works in its physical layer, which can not only work alone, but also assist the traditional communication network security mechanism, so as to provide higher security performance for the communication network. Similarly, when identifying sonar transmitters, we also identify individuals by extracting subtle differences in the Countermeasures in the output signals of sonar transmitters. We think that the extracted features should have five characteristics: universality, uniqueness, short-term invariance, independence and robustness. It is a physical layer method to protect the security of communication system. Different sonar devices have different subtle characteristics and can be used for identification and access authentication of sonar devices.

II. RELATED WORK

A. BEHAVIOR MODELING

The nonlinearity of sonar transmitter results in the unintentional modulation of the sonar signal. This unintentional modulation is closely related to the individual differences of amplifiers. Extracting these features from signals can identify individuals effectively.

The nonlinear behavior modeling of nonlinear system can be classified into two categories: memoryless behavioral models and behavioral models with memory. The memoryless model has a good fitting effect for some specific nonlinear systems and narrowband communication systems. However, With the rapid development of wireless communication technology, the bandwidth of wireless signals is wider and wider, the signal frequency is getting higher and higher, and the memory effect of wireless signals cannot be ignored. Therefore, scholars' research focuses on memory models.

In 2011, Ming-Wei Liu et al. analyzed the nonlinearity of a kind of circuit in front-end nonlinearity device of communication equipment. Because the nonlinearity of the circuit leads to spectrum regeneration, distortion of communication signal waveform and widening of signal spectrum [12]–[14]. These phenomena are related to the individual differences of hardware, which makes it possible to identify individual emitters. In document [15], the influence of noise and input power on power amplifier is simulated, and the change model is established. The coefficient of the non-linear model is extracted by spectral regeneration [15].

After observing signals of a certain length of time, this method can identify the source of communication radiation under the condition of high signal-to-noise ratio. Alternatively, the excellent capability of artificial neural networks(ANNs) to accurately approximate continuous functions has been successfully exploited to model nonlinear system [16]–[19].

In document [20], the author proposed a two hidden layers artificial neural networks models to fit the dynamic nonlinear behavior of a 250-W Doherty amplifier driven with a 20-MHz bandwidth.

In document [21], a comparative study of behavioral models for microwave power amplifiers is proposed. The author analyzed the fitting accuracy and computational complexity of multiple behavioral models, including Volterra series model, memory polynomial, Volterra with dynamic deviation reduction, generalized memory polynomial model and Kautz˘Volterra and Laguerre˘Volterra model. Two PAs were studied to compare the performance of these models and the results shows that the generalized memory polynomial behavioral model has the best tradeoff for accuracy versus complexity for both PAs.

This paper will model the behavior of power amplifier circuit in sonar transmitter, simulate sonar transmitter with the same model, the same batch of production and the same mode of operation for steady-state characteristic analysis, and extract fine features that can be used for individual classification and recognition of sonar transmitter.

B. INDIVIDUAL RECOGNITION TECHNOLOGY

Due to the inherent nonlinearities of the power amplifiers of sonar transmitters, these feature provide distinguish features for sonar transmitter recognition. In [22], [23], the author used 3 order Taylor polynomial to model the amplifiers. Four similar amplifiers are simulated by behavioral models derived from four approximate parameters. The paper proposed an transmitter recognition method based on variational mode decomposition and spectral features, which is comparing with empirical mode decomposition. And different spectral features, including spectral flatness, spectral brightness, and spectral roll-off are used to improve the recognition rate.

In [24],the author proposed a sparse feature learning method beyond manual design is proposed to learn features from the samples sampled during tracking.

In [25], a communication radiation source individual identification method based on dimensional reduction and machine learning is proposed as a component of intrusion detection for resolving authentication security issues. The authors compared three kinds of dimensional reduction methods, which are the traditional PCA, RPCA and KPCA [26], [27].

And this paper take random forests, support vector machine, artificial neural network and grey correlation analysis into consideration to make decisions on the dimensional reduction data [28], [29].

In [8], the power spectrum estimation is used to distinguish different Universal Software Radio Peripherals(USRPs). In [30], 40 identical ZigBee devices are the research object of transmitter recognition. The feature this paper used is power spectrum estimation. In this paper, the power spectrum estimation of the sonar transmitter output signals based on Welch method is used to identify different sonar transmitters

III. METHOD OVERVIEW

This section mainly introduces the memory polynomial model and power spectral density characteristics used in this paper.

A. MEMORY POLYNOMIAL MODEL

Power amplifiers with memory refers to the output of power amplifier at a certain time not only related to the input at this time, but also related to the input at a certain time before [31]. The polynomial model of memoryless power amplifier is dispersed and expressed as follows.

$$y(n) = \sum_{k=1}^{K} h_k z^k(n) = h_1 z(n) + h_2 z^2(n) + \cdots + h_K z^K(n) \qquad n = 1, 2, \cdots N \tag{1}$$

Increasing Memory Effect on Formula 1, the model can be expressed as follows.

$$\begin{aligned} y(n) &= \sum_{k=1}^{K}\sum_{m=0}^{M} h_{km} z^k(n-m) \\ &= h_{10}z(n) + h_{11}z(n-1) + \cdots + h_{1M}z(n-M) \\ &\quad + h_{20}z^2(n) + h_{21}z^2(n-1) + \cdots h_{2M}z^2(n-M) \\ &\quad + \cdots \\ &\quad + h_{K0}z^K(n) + h_{K1}z^K(n-1) + \cdots h_{KM}z^K(n-M) \\ n &= 1, 2, \cdots N \end{aligned} \tag{2}$$

where, K is the nonlinear order and M is the memory depth. The formula (2) can be simplified to formula (3)

$$y(n) = \sum_{k=1}^{K}\sum_{m=0}^{M} h_{km} z(n-m)|z(n-m)|^{k-1} \qquad n = 1, 2 \cdots N \tag{3}$$

Next, we calculate the coefficients of the model. Firstly, we define $z_{km}(n) = z(n-m)|z(n-m)|^{k-1}$ and $z_{km} = [z_{km}(1), z_{km}(2), \cdots, z_{km}(n)]^T$. Then, we rewrite formula (2) into a matrix form.

$$y = Zh \tag{4}$$

where,

$$y = [y(1), \cdots, y(n)]^T \tag{5}$$

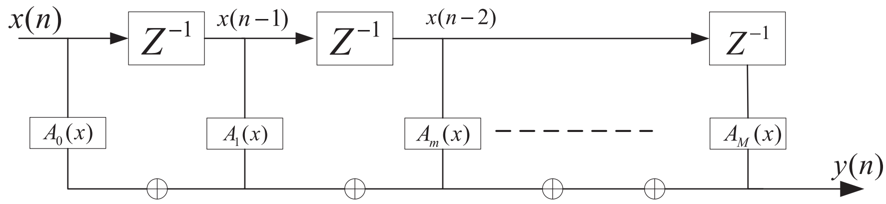


FIGURE 2. A block diagram of the memory polynomial model.

$$Z = [z_{10}, \cdots z_{K0}, z_{11}, \cdots z_{K1}, \cdots z_{1M}, \cdots z_{KM}] \tag{6}$$

$$h = [h_{10}, \cdots h_{K0}, h_{11}, \cdots h_{K1}, \cdots h_{1M}, \cdots h_{KM}]^T \tag{7}$$

We introduce a polynomial model based on orthogonal basis function and rewrite formula (4) into formula (8).

$$y = \psi c \tag{8}$$

where, ψ is a group of orthogonal bases and it is a $K \times M$ order matrix. By using the least square method, we can get the analytical expression of the model coefficients.

$$\hat{c}_{LS} = (\psi^T \psi)^{-1} \psi^T y \tag{9}$$

Figure 2 show that a block diagram of the memory polynomial model.

B. POWER SPECTRUM DENSITY ESTIMATION

The power spectral function represents the frequency function of the unit bandwidth power with the spectrum component of the finite average power signals [32]. The important characteristics of the random signal are studied and analyzed. Power spectrum estimation is one of the main contents of signal processing. It mainly studies the characteristics of signal in frequency domain. In this paper, the power spectrum estimation of the sonar transmitter output signals based on Welch method is used.

Periodogram method assumes that $x_i(n)(i = 0, 1, \cdots K-1)$ is the uncorrelated implementation of stochastic process $x(n)$. The length of every $x_i(n)$ is M. The periodogram of $x_i(n)$ is:

$$P_{per}^{(i)}(e^{i\omega}) = \frac{1}{M}\left|\sum_{n=0}^{M-1} x_i(n)e^{-j\omega n}\right|^2 \quad i = 1, 2, \cdots K \tag{10}$$

Then, computing the average of these independent periodogram and the result is the estimation of power spectrum as shown below.

$$P_{per}^{(av)}(e^{j\omega}) = \frac{1}{K} P_{per}^{(i)}(e^{j\omega}) \tag{11}$$

In application, it is seldom to get repeatedly implementations of a random signal. Accordingly, Bartlett proposed dividing a random signal with length N into K segments on average. Further, define every sub signal as $x_i(n) = x(n + iM)(n = 0, 1, \cdots M - 1; i = 0, 1, \cdots K - 1)$ And, computing the periodogram of every sub signal and computing the average. Final, the expression of average periodogram is:

$$P_{per}^{(BT)}(e^{j\omega}) = \frac{1}{M}\sum_{i=0}^{K-1}\left|\sum_{n=0}^{M-1} x(n + iM)e^{-j\omega n}\right|^2 \tag{12}$$

Welch's method has two modifications to the average periodogram method.

- The Welch's method improves segmentation scheme of $x(n)$. The method allows a certain degree of overlap between the data of each segment and its adjacent data segment. For example, when the data of each segment coincides with half of the segment, the number of segment turn into $K = N - (M/2)/M/2$. Where, M is the length of each segment of data, N is the total length of the data.
- Data windowing for each segment may not be a rectangular window. Such as Hanning window and Hamming window. This can improve the distortion caused by the larger side lobe of rectangular window.

The expression of power spectrum estimation based on Welch's method is:

$$P_w^{(i)}(e^{j\omega}) = \frac{1}{MU}\left|\sum_{n=0}^{M-1} x_i(n)\omega(n)e^{-j\omega n}\right|^2 \tag{13}$$

where $\omega(n)$ is a window function, $x_i(n)$ represents the i-segment data sequence.

IV. EXPERIMENT AND RESULTS

A. EXPERIMENT STEPS

Sonar transmitter belongs to low-frequency radiation source, which is an important part of the sonar system. It transmits sound wave information into water. The frequency is from several hundred Hz to several hundred KHz, and the transmitted signal is usually a continuous wave signal. In this experiment, we firstly use a memory polynomial method to model the sonar transmitter.

The experiment steps are shown in figure 3. In this paper, the non-linear order of memory polynomial is 3 and the memory depth is 3.

Then, we slightly change the parameters of the model to get a similar transmitter model. Next, we input the same signal to the model and get its output data through the model. The model parameters are shown in the table 1. Finally, we extract the features from the output data to realize the classification and recognition of transmitter individuals.

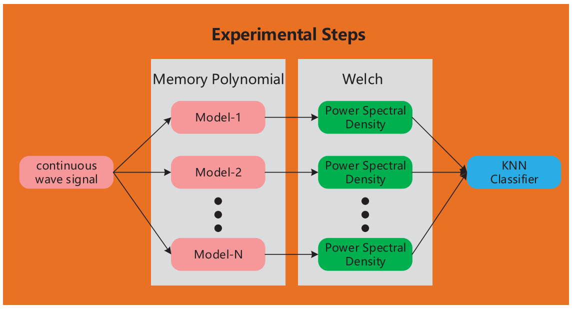


FIGURE 3. The experiment steps.

TABLE 1. The parameters of the models.

Number	h_1	h_2	h_3	h_4	h_5	h_6
No.1	3.00	1.98	0.70	0.02	0.02	0.01
No.2	3.00	1.91	0.80	1.04	0.04	0.02
No.3	3.00	1.89	0.70	0.08	0.06	0.03
No.4	3.00	1.85	0.90	0.06	0.08	0.05
No.5	3.00	1.78	0.80	1.04	0.02	0.02

B. RESULTS

Firstly, we compared signals passing through linear and non-linear systems. Figure 4 shows that the power spectrum estimation of the output signals of linear and nonlinear systems with single tone input.

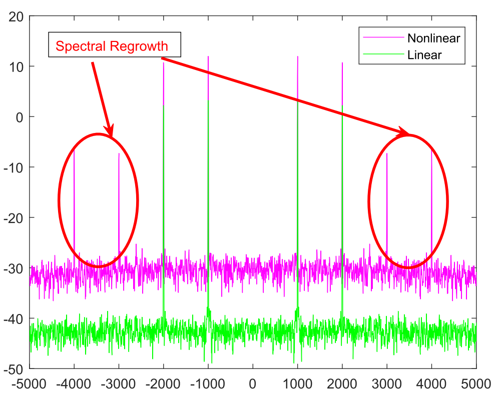
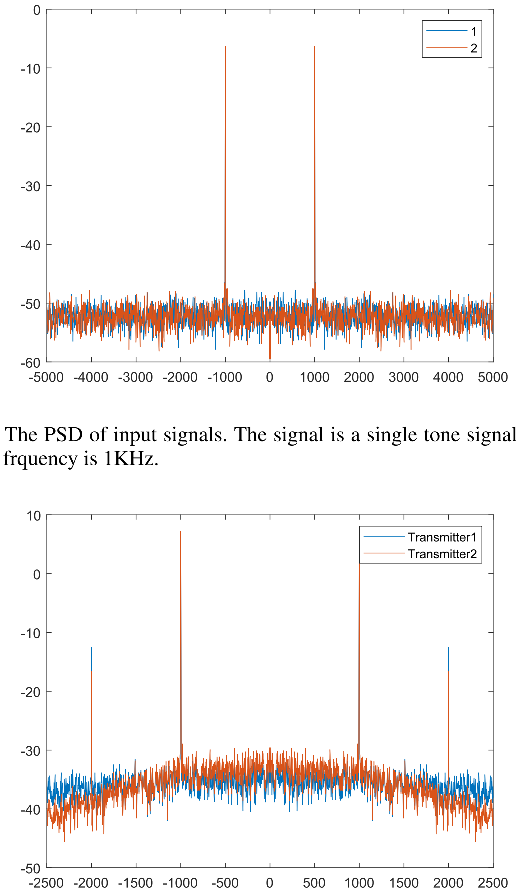


FIGURE 4. The power spectrum estimation of the output signals of linear and nonlinear systems.

As we can seen, after the signal passes through the non-linear system, it shows obvious non-linear characteristics. That is spectral regrowth phenomenon. This nonlinearity limits the delivered output power because of the compression nonlinear characteristics and also introduces unwanted signal components at the output of the nonlinear device. These unwanted signal components are called ''nonlinear distortion'' that is manifested as harmonics at multiples of the fundamental frequencies when the input signal consists of discrete tones and, as spectral regrowth when the input signal spectrum has a finite bandwidth. We can utilize the nonlinear distortion of different transmitters to distinguish these transmitters.



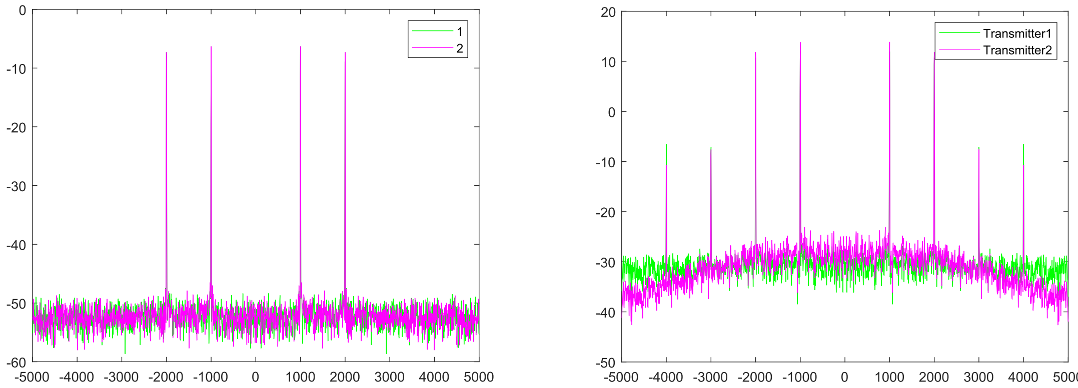
(a) The PSD of input signals. The signal is a single tone signal and the frquency is 1KHz.

(b) The PSD of output signals.

FIGURE 5. Power spectrum estimation comparison of model input and output signals. The input signal is single-tone signal and the frequency is 1KHz. The signal is a single tone signal and the frequency is 1KHz.

Secondly, we compared the power spectrum estimation of different transmitters. We input the same single signal and two tone signal to two transmitters. Figure 5 shows that the power spectrum estimation comparison of the output signals of two different models. The input signal is single-tone signal and the frequency is 1KHz. Figure 6 shows that the power spectrum estimation comparison of the output signals of two different models and the input signal is two-tone signal and the frequency are 1KHz and 2KHz. As we can see, when the input signal is two-tone signal, the nonlinearity of the output of the model is more obvious. Therefore, we assume that it is easier to distinguish different transmitters when the input signal of the transmitters is two-tone signal.

Figure 7 shows that the curve of recognition results with SNR under different input signals. The results shows that power spectrum estimation can distinguish these transmitters and it is easier to distinguish different transmitters when the input signal of the transmitters is two-tone signal. When the input signal is two tone signal, the recognition rate can reach 100% when the SNR is 0dB.



(a) The PSD of input signal. (b) The PSD of output signals.

FIGURE 6. **Power spectrum estimation comparison of model input and output signals. The input signal is two-tone signal and the frequency are 1KHz and 2KHz.**

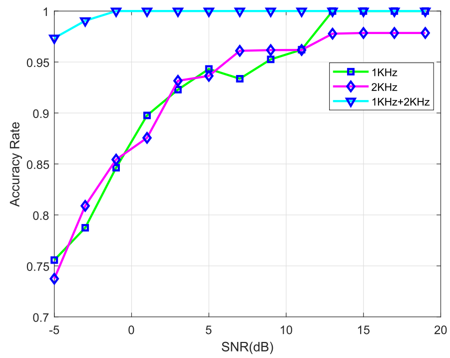


FIGURE 7. **The curve of recognition results with SNR under different input signals.**

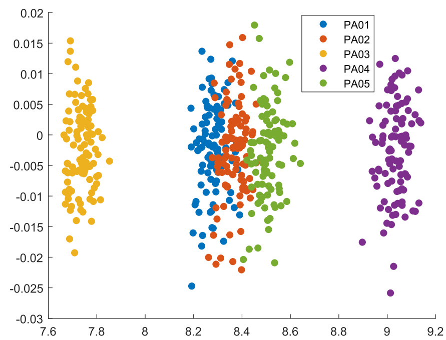


FIGURE 8. **The feature visualization of five transmitter with SNR is 10dB. The input signal is single-tone signal.**

We use principal component analysis to reduce the dimension of the feature vector. Figure 8 shows that feature visualization of five transmitter with the input signal is single-tone signal and the SNR is 10dB. Figure 9 shows that feature visualization of five transmitter with the input signal is two-tone signal and the SNR is 10dB. As we can see, at the same signal-to-noise ratio, when the input signal is a dual-tone signal, the five similar transmitter models have better discrimination.

TABLE 2. **The case overview.**

Item	instruction
Feature selection	Power spectrum estimation
Transmitter selection	Nonlinear model of sonar transmitter
Input signal	1KHz single tone // 2KHz single tone 1KHz +2KHz two tone
Communication channel	AWGN channel(SNR = -5−20dB)
Sampling rates	10KHz
Number of FFT points	2048 points
Number of transmitters	5
Number of the signal samples	100 samples per user
Number of the points per samples	10000 points per samples

Then, we utilize five nonlinear models as five sonar transmitters to verify the validity of our method. The detailed experiment conditions are shown in table 2.

We mainly analyze whether similar transmitters can be distinguished by power spectrum estimation and the influence of different input signals on the recognition results.

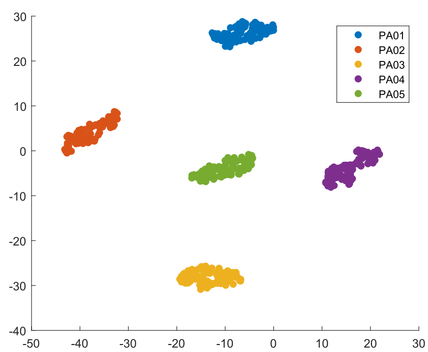


FIGURE 9. **The feature visualization of five transmitter with SNR is 10dB. The input signal is two-tone signal.**

V. CONCLUSION

This paper mainly studies the individual identification of emitter based on the behavior modeling of the sonar transmitter. Ten approximate sonar transmitters are obtained by memory polynomial modeling. The same signals are input to the sonar transmitter model to collect its output signals, and the output signals are extracted feature and classified. In this paper, the memory polynomial method is used to model the behavior of sonar transmitter, and the power spectrum estimation of the output signals are used as the fingerprint feature to identify the transmitters. The experimental results show that this method can effectively identify multiple similar sonar transmitters.

In the future, we will consider more signals of the sonar transmitter and other relevant wireless network devices. The underwater environment factors will be considered to improve the system.

REFERENCES

[1] G. Han, J. Jiang, L. Shu, and M. Guizani, "An attack-resistant trust model based on multidimensional trust metrics in underwater acoustic sensor network," *IEEE Trans. Mobile Comput.*, vol. 14, no. 12, pp. 2447–2459, Dec. 2015.

[2] G. Han, J. Jiang, N. Bao, L. Wan, and M. Guizani, "Routing protocols for underwater wireless sensor networks," *IEEE Commun. Mag.*, vol. 53, no. 11, pp. 72–78, Nov. 2015.

[3] G. Han, J. Jiang, N. Sun, and L. Shu, "Secure communication for underwater acoustic sensor networks," *IEEE Commun. Mag.*, vol. 53, no. 8, pp. 54–60, Aug. 2015.

[4] Y. Lin, H. Tao, Y. Tu, and T. Liu, "A node self-localization algorithm with a mobile anchor node in underwater acoustic sensor networks," *IEEE Access*, vol. 7, pp. 43773–43780, 2019.

[5] L. C. C. Desmond, C. C. Yuan, C. P. Tan, and R. S. Lee, "Identifying unique devices through wireless fingerprinting," in *Proc. 1st ACM Conf. Wireless Netw. Secur.*, Mar. 2008, pp. 46–55.

[6] D. R. Reising, M. A. Temple, and J. A. Jackson, "Authorized and rogue device discrimination using dimensionally reduced RF-DNA fingerprints," *IEEE Trans. Inf. Forensics Security*, vol. 10, no. 6, pp. 1180–1192, Jun. 2015.

[7] S. D'Agostino, "Specific emitter identification based on amplitude features," in *Proc. IEEE Int. Conf. Signal Image Process. Appl. (ICSIPA)*, Kuala Lumpur, Malaysia, Oct. 2015, pp. 350–354.

[8] W. Wang, Z. Sun, S. Piao, B. Zhu, and K. Ren, "Wireless physical-layer identification: Modeling and validation," *IEEE Trans. Inf. Forensics Security*, vol. 11, no. 9, pp. 2091–2106, Sep. 2016.

[9] C. Bertoncini, K. Rudd, B. Nousain, and M. Hinders, "Wavelet fingerprinting of radio-frequency identification (RFID) tags," *IEEE Trans. Ind. Electron.*, vol. 59, no. 12, pp. 4843–4850, Dec. 2012.

[10] W. Wang, Z. Sun, K. Ren, and B. Zhu, "User capacity of wireless physical-layer identification," *IEEE Access*, vol. 5, pp. 3353–3368, 2017.

[11] J. Hall, M. Barbeau, and E. Kranakis, "Detection of transient in radio frequency finger printing using signal phase," in *Proc. IASTED Int. Conf. Wireless Opt. Commun.*, Calgary, AB, Canada, Jul. 2003, pp. 13–18.

[12] M.-W. Liu and J. F. Doherty, "Nonlinearity estimation for specific emitter identification in multipath channels," *IEEE Trans. Inf. Forensics Security*, vol. 6, no. 3, pp. 1076–1085, Sep. 2011.

[13] M.-W. Liu and J. F. Doherty, "Specific emitter identification using nonlinear device estimation," in *Proc. IEEE Sarnoff Symp.*, Princeton, NJ, USA, Apr. 2008, pp. 1–5.

[14] M.-W. Liu and J. F. Doherty, "Wireless device identification in MIMO channels," in *Proc. 43rd Annu. Conf. Inf. Sci. Syst.*, Baltimore, MD, USA, Mar. 2009, pp. 563–567.

[15] J. C. Pedro and S. A. Maas, "A comparative overview of microwave and wireless power-amplifier behavioral modeling approaches," *IEEE Trans. Microw. Theory Techn.*, vol. 53, no. 4, pp. 1150–1163, Apr. 2005.

[16] Y. Fang, M. C. E. Yagoub, F. Wang, and Q.-J. Zhang, "A new macromodeling approach for nonlinear microwave circuits based on recurrent neural networks," *IEEE Trans. Microw. Theory Techn.*, vol. 48, no. 12, pp. 2335–2344, Dec. 2000.

[17] H. Songbai, Y. Xiaohuan, and B. Jingfu, "Applications of feedforward neural networks to WCDMA power amplifier model," in *Proc. Asia–Pacific Microw. Conf.*, Dec. 2005, p. 3.

[18] J. Wood, M. LeFevre, D. Runton, J.-C. Nanan, B. H. Noori, and P. H. Aaen, "Envelope-domain time series (ET) behavioral model of a Doherty RF power amplifier for system design," *IEEE Trans. Microw. Theory Techn.*, vol. 54, no. 8, pp. 3163–3172, Aug. 2006.

[19] A. Ahmed, E. R. Srinidhi, and G. Kompa, "Efficient PA modeling using neural network and measurement setup for memory effect characterization in the power device," in *IEEE MTT-S Int. Microw. Symp. Dig.*, Jun. 2005, pp. 473–476.

[20] F. Mkadem and S. Boumaiza, "Physically inspired neural network model for RF power amplifier behavioral modeling and digital predistortion," *IEEE Trans. Microw. Theory Techn.*, vol. 59, no. 4, pp. 913–923, Apr. 2011.

[21] A. S. Tehrani, H. Cao, S. Afsardoost, T. Eriksson, M. Isaksson, and C. Fager, "A comparative analysis of the complexity/accuracy tradeoff in power amplifier behavioral models," *IEEE Trans. Microw. Theory Techn.*, vol. 58, no. 6, pp. 1510–1520, Jun. 2010.

[22] U. Satija, N. Trivedi, G. Biswal, and B. Ramkumar, "Specific emitter identification based on variational mode decomposition and spectral features in single hop and relaying scenarios," *IEEE Trans. Inf. Forensics Security*, vol. 14, no. 3, pp. 581–591, Mar. 2019.

[23] J. Zhang, F. Wang, O. A. Dobre, and Z. Zhong, "Specific emitter identification via Hilbert –Huang transform in single-hop and relaying scenarios," *IEEE Trans. Inf. Forensics Security*, vol. 11, no. 6, pp. 1192–1205, Jun. 2016.

[24] M. Jia, Z. Gao, Q. Guo, Y. Lin, and X. Gu, "Sparse feature learning for correlation filter tracking toward 5G-enabled tactile Internet," *IEEE Trans. Ind. Informat.*, to be published.

[25] Z. Dou, G. Si, Y. Lin, and M. Wang, "An adaptive resource allocation model with anti-jamming in IoT network," *IEEE Access*, to be published.

[26] Z. Zhang, X. Guo, and Y. Lin, "Trust management method of D2D communication based on RF fingerprint identification," *IEEE Access*, vol. 6, pp. 66082–66087, 2018.

[27] Y. Lin, X. Zhu, Z. Zheng, Z. Dou, and R. Zhou, "The individual identification method of wireless device based on dimensionality reduction and machine learning," *J. Supercomput.*, vol. 75, no. 6, pp. 3010–3027, Jun. 2019.

[28] J. Li, D. Bi, Y. Ying, K. Wei, and B. Zhang, "An improved algorithm for extracting subtle features of radiation source individual signals," *Electronics*, vol. 8, no. 2, p. 246, Feb. 2019.

[29] Y. Tu, Y. Lin, J. Wang, and J.-U. Kim, "Semi-supervised learning with generative adversarial networks on digital signal modulation classification," *Comput., Mater. Continua*, vol. 55, no. 2, pp. 243–254, 2018.

[30] W. Wang, Z. Sun, K. Ren, and B. Zhu, "User capacity of wireless physical-layer identification: An information-theoretic perspective," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Kuala Lumpur, Malaysia, May 2016, pp. 1–6.

[31] A. R. Belabad, S. A. Motamedi, and S. Sharifian, "A novel generalized parallel two-box structure for behavior modeling and digital predistortion of RF power amplifiers at LTE applications," *Circuits, Syst., Signal Process.*, vol. 37, no. 7, pp. 2714–2735, Jul. 2018.

[32] P. O'Shea, "The use of sliding spectral windows for parameter estimation in power system disturbance monitoring," *IEEE Trans. Power Syst.*, vol. 15, no. 4, pp. 1261–1267, Nov. 2000.

FAN SHI received the B.S. degree in transportation and the M.S. and Ph.D. degrees in power machinery and engineering from Harbin Engineering University, Harbin, China, in 2003, 2006, and 2009, respectively. From 2009 to 2011, he was a Senior Engineer with PERA GLOBAL, Harbin. From 2011 to 2015, he was a Senior Engineer with the SANY Group, Suzhou, China. From 2015 to 2016, he was a Researcher with the Zhejiang Marine Development Research Institute, Zhoushan, China. In 2016, he joined Ningbo University, Ningbo, China, where he is currently a Lecturer with the Faculty of Maritime and Transportation. His research interests include ocean environment signal processing, power machinery performance test, and ocean engineering structure analysis.

ZHENLEI CHEN received the Ph.D. degree from the University of Illinois at Chicago, in 2000. He became a Senior Engineer at Powertrain Engine Engineering, Ford Motor Company, USA. In 2012, he was a Technical Director and the Vice President of the research institute with Sany Heavy Machinery Company, Ltd., China. In 2016, he was appointed as a Professor with Ningbo University, China. His research interests include ocean environment signal processing and ocean engineering structure analysis.

XIAOCHUN CHENG (SM'04) received the bachelor's degree in computer engineering and the Ph.D. degree in computer science from Jilin University, in 1992 and 1996, respectively. He has been a Computer Science EU Project Coordinator with Middlesex University, since 2012. He is a member of the IEEE SMC Technical Committee on Enterprise Information Systems, the IEEE SMC Technical Committee on Computational Intelligence, the IEEE SMC Technical Committee on Cognitive Computing, the IEEE SMC Technical Committee on Intelligent Internet Systems, the IEEE Communications Society Communications and Information Security Technical Committee, the BCS Information Security Specialist Group, the BCS Cybercrime Forensics Specialist Group, and the BCS Artificial Intelligence Specialist Group.