Shi, Fan, Chen, Zhenlei and Cheng, Xiaochun (2019) Behaviour modelling and individual recognition of sonar transmitter for secure communication in UASNs. IEEE Access, 2019. ISSN 2169-3536 (Published online first)

Final accepted version (with author's formatting)

This version is available at: http://eprints.mdx.ac.uk/26818/

Copyright:

Middlesex University Research Repository makes the University's research available electronically.

Copyright and moral rights to this work are retained by the author and/or other copyright owners unless otherwise stated. The work is supplied on the understanding that any use for commercial gain is strictly forbidden. A copy may be downloaded for personal, non-commercial, research or study without prior permission and without charge.

Works, including theses and research projects, may not be reproduced in any format or medium, or extensive quotations taken from them, or their content changed in any way, without first obtaining permission in writing from the copyright holder(s). They may not be sold or exploited commercially in any format or medium without the prior written permission of the copyright holder(s).

Full bibliographic details must be given when referring to, or quoting from full items including the author's name, the title of the work, publication details where relevant (place, publisher, date), pagination, and for theses or dissertations the awarding institution, the degree type awarded, and the date of the award.

If you believe that any material held in the repository infringes copyright law, please contact the Repository Team at Middlesex University via the following email address:

eprints@mdx.ac.uk

The item will be removed from the repository while any claim is being investigated.

See also repository copyright: re-use policy: http://eprints.mdx.ac.uk/policies.html#copy
Behavior Modeling and Individual Recognition of Sonar Transmitter for Secure Communication in UASNs

FAN SHI1, ZHENLEI CHEN1, AND XIAOCHUN CHENG2.

1Faculty of Maritime and Transportation, Ningbo University, Ningbo 315211, China (e-mail: baqingshifan@126.com)
2Department of Computer Science, Middlesex University, London, UK, NW4 4BT (e-mail: X.Cheng@mdx.ac.uk)

Corresponding author: ZHENLEI CHEN (e-mail: artchenzhenlei@126.com).

This research is supported by the K.C. Wong Magna Fund in Ningbo University.

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 non-linear 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. Firstly, the non-linearity of the sonar transmitter is studied in depth, and the non-linearity of the power amplifier is modeled and its non-linearity 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 non-linear characteristics of the signal. By this way, this method can enhance the communication safety of UASNs.

INDEX TERMS Specific Emitter Identification, Sonar, Nonlinear Model, Power Amplifier

I. INTRODUCTION

The underwater 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, shipwreck rescue, underwater testing, ancient and marine disaster warn-
ings[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.

![Figure 1: The power spectrum estimation of the output signals of linear and nonlinear systems.](image)

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 can not 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]-[15].
These phenomena are related to the individual differences of hardware, which makes it possible to identify individual emitters. In document [16], 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 [16].

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 systems [17]-[20].

In document [21], 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 [22], 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 complexity for both PAs.

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 [29][30].

In [31], the power spectrum estimation is used to distinguish different Universal Software Radio Peripherals (USRPs). In [32], 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 [33]. The polynomial model of memoryless power amplifier is dispersed and expressed as follows.

\[
y(n) = \sum_{k=1}^{K} h_k z^k(n) = h_1 z(n) + h_2 z^2(n) + \cdots + h_K z^K(n) 
\]

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

\[
y(n) = \sum_{k=1}^{K} \sum_{m=0}^{M} h_{km} z^{k}(n-m) = h_{10} z(n) + h_{11} z(n-1) + \cdots + h_{1M} z(n-M) + h_{20} z^2(n) + h_{21} z^2(n-1) + \cdots + h_{2M} z^2(n-M) + \cdots + h_{K0} z^K(n) + h_{K1} z^K(n-1) + \cdots + h_{KM} z^K(n-M) 
\]

\[n = 1, 2, \cdots N\]

(2)

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

\[
y(n) = \sum_{k=1}^{K} \sum_{m=0}^{M} h_{km} z^{(n-m)} z^{(n-m)} \Big|^{k-1} 
\]

\[n = 1, 2, \cdots N\]

(3)

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

\[
y = Zh
\]

(4)

Where,

\[
y = [y(1), \cdots, y(n)]^T
\]

(5)

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

(6)

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

(7)
We introduce a polynomial model based on orthogonal basis function and rewrite formula (4) into formula (8).

\[ y = \psi c \]  

(8)

where, \( \psi \) 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.

\[ \hat{c}_{LS} = (\psi^T \psi)^{-1} \psi^T y \]  

(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[34]. 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:

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

(10)

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

\[ P_{per}^{(av)}(e^{j\omega}) = \frac{1}{K} P_{per}^{(i)}(e^{j\omega}) \]  

(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. The expression of average periodogram is:

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

(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:

\[ P_{per}^{(i)}(e^{j\omega}) = \frac{1}{MU} \left| \sum_{n=0}^{M-1} x_i(n)w(n)e^{-j\omega n} \right|^2 \]  

(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.

**TABLE 1.** The parameters of the models

<table>
<thead>
<tr>
<th>Number</th>
<th>( h_1 )</th>
<th>( h_2 )</th>
<th>( h_3 )</th>
<th>( h_4 )</th>
<th>( h_5 )</th>
<th>( h_6 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>No.1</td>
<td>3.00</td>
<td>1.98</td>
<td>0.70</td>
<td>1.04</td>
<td>0.02</td>
<td>0.02</td>
</tr>
<tr>
<td>No.2</td>
<td>3.00</td>
<td>1.91</td>
<td>0.80</td>
<td>1.04</td>
<td>0.04</td>
<td>0.02</td>
</tr>
<tr>
<td>No.3</td>
<td>3.00</td>
<td>1.89</td>
<td>0.70</td>
<td>0.08</td>
<td>0.06</td>
<td>0.03</td>
</tr>
<tr>
<td>No.4</td>
<td>3.00</td>
<td>1.85</td>
<td>0.90</td>
<td>0.06</td>
<td>0.08</td>
<td>0.05</td>
</tr>
<tr>
<td>No.5</td>
<td>3.00</td>
<td>1.78</td>
<td>0.80</td>
<td>1.04</td>
<td>0.02</td>
<td>0.02</td>
</tr>
</tbody>
</table>

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.
B. RESULTS

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

![Figure 4](image)

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

As we can see, after the signal passes through the nonlinear 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.

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 5](image)

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

![Figure 6](image)

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

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.

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 single-tone signal, the five similar transmitter models have better discrimination.

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.

<table>
<thead>
<tr>
<th>Item</th>
<th>Instruction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Feature selection</td>
<td>Power spectrum estimation</td>
</tr>
<tr>
<td>Transmitter selection</td>
<td>Nonlinear model of sonar transmitter</td>
</tr>
<tr>
<td>Input signal</td>
<td>1KHz single tone / 2KHz single tone</td>
</tr>
<tr>
<td>Communication channel</td>
<td>AWGN channel (SNR = -5–20dB)</td>
</tr>
<tr>
<td>Sampling rates</td>
<td>10KHz</td>
</tr>
<tr>
<td>Number of FF1 points</td>
<td>2048 points</td>
</tr>
<tr>
<td>Number of transmitters</td>
<td>5</td>
</tr>
<tr>
<td>Number of the signal samples</td>
<td>100 samples per user</td>
</tr>
<tr>
<td>Number of the points per samples</td>
<td>10000 points per samples</td>
</tr>
</tbody>
</table>

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

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 future work, we will consider collecting actual signals of the sonar transmitter and other wireless network devices. The environment of underwater will be considered in future work.

ACKNOWLEDGMENT

This research is supported by the K.C. Wong Magna Fund in Ningbo University.

REFERENCES

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.

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

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

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

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


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 with PERA GLOBAL, Harbin, as a Senior Engineer. From 2011 to 2015, he was with the SANY Group, Suzhou, China, as a Senior Engineer. From 2015 to 2016, he was with the Zhejiang Marine Development Research Institute, Zhoushan, China, as a Researcher. 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 earned his doctoral degree at the University of Illinois at Chicago in May 2000. Thereafter he became a senior engineer at powertrain engine engineering of Ford motor company, USA. In May 2012 he was employed by Sany heavy machinery Co. Ltd. China, acting as a technical director and vice president of the research institute. In May 2016 he was appointed as a professor of Ningbo University in China. His research interests include ocean environment signal processing and ocean engineering structure analysis.

***