International Journal of Multimedia and Ubiquitous Engineering
Vol.10, No.10 (2015), pp.75-82
http://dx.doi.org/10.14257/ijmue.2015.10.10.08

DPOAE Biological Feature Modeling and Identity Authentication

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Abstract

In this article, a multi-tone signal generated by micro-speaker is adopted as the acoustic stimulation, and two microphones are used to collect the DPOAE data from human ear and background noise respectively. Otoacoustic emission is modeled based on Volterra kernel. The feature of human ear's DPOAE feature model is extracted intelligently by improved stimulation annealing genetic mixed algorithm. In order to apply this model feature to identification, its feasibility is verified by BP neural network. This provides a new biometric method for identity authentication.

Keywords: *DPOAE, modeling, biological features, Feature Extraction, Identity authentication*

1. Introduction

Identity authentication is required not only for high-confidential activities like banking services, entering secret institutions or searching for certain technical and economic resources, but also for various daily applications like taking attendance at workplace and entering the residence building for security reasons. In short, identity authentication is widely used in a vast range of fields including economic, military and daily usage and this has given rise to the popularity of fingerprint, face or iris recognition technologies. With the increasing popularity of such identity authentication techniques, however, a problem arises. People's identity are stolen through methods like making copies of peoples fingerprints or even iris, which poses huge economic loss to both families and the nation as a whole. Therefore, looking for substitutable biological features which can provide a more secured and reliable identification has become a pressing issue. This has lead to the development of the technique of 'detecting the characteristic of OAE' which will be discussed in detail in the later part of this paper.

Otoacoustic emissions are a physiological function of the human ear. When cochlea is stimulated by two pure tones which has a certain frequency ratio and intensity ratio, cochlear active mechanism will produce various forms of distortion, the otoacoustic emission signal which is detected in external acoustic meatus is called DPOAE(distortion product otoacoustic emission) [1]. DPOAE has been widely used in children hearing screening and early diagnosis of hearing impairment in adults [2]. It has the characteristics of repeatability, long term stability, and individual differences and so on.

In this paper, on top of collecting the DPOAE data, the Volterra kernel is used to build the DPOAE characteristics model of ear, in order to discuss the feasibility of the use of biometric for identification. Imagining this technique being applied in your residential door lock, the door will open automatically after you put on a specially-made earphone, then you are able to enjoy your comfortable home knowing that your house is well-secured.

ISSN: 1975-0080 IJMUE

2. DPOAE and its Detection

There are a variety of otoacoustic emissions, TEOAE (Transient Evoked Otoacoustic Emission) and DPOAE has been used more frequently in clinical application. In terms of detecting speed and accuracy, DPOAE outraces TEOAE, so DPOAE has been more widely used in actual application [3].

If we use the frequencies f1 and f2 which are pure pulse as the stimulus of DPOAE, the amplitudes of DPOAE are larger among the frequencies of 2f2-f1、2f1-f2、3f1-2f2 and 4f1-3f2, especially in the frequency of 2f1-f2, and the number of its occurrences is the most [4-5]. Normally, DPOAE occurs in a few milliseconds after the inducing stimulus, the amplitudes are much smaller compared to the inducing stimulus, the two of them differ by about 1000 times, we can use the entire period sampling method to prevent it from being blocked by the induced stimulating sound [6]. In addition, there are many factors affecting the amplitude values of DPOAE. For example, the respective frequencies and frequency ratios, intensity and intensity difference values of two stimulus sound. Normally, the two induced sound frequency ratio ranges from 1.22 to 1.25, and their intensity values are around 70dB SPL, so that a DPOAE signal with larger amplitude can be obtained [7].

DPOAE shows that the cochlear active mechanism is a nonlinear process. Therefore, in our study we designs the measurement sensor according to the characteristics of DPOAE, process the measured data and use the Volterra kernel model to describe the characteristics [8-9].

3. DPOAE Signal Acquisition Sensor and its Measurement Channel

In order to achieve high accuracy in the DPOAE measurement, sensors should have the functions of generating test stimulation, detecting otoacoustic emission, as well as testing environmental noise. Therefore, a three-element sensor which consists of a loudspeaker and two microphones will be used in our study.

The sensor includes several parts: a background-sound-collecting microphone which acquire the background sound from the surroundings, a sound collecting microphone within the ear used to measure the sound within the ear canal, and a micro loudspeaker used to generate acoustic stimulation.

The sensor on the front-end and the measurement circuit are used to accomplish the acquisition of DPOAE signal which is then processed by the computer. The diagram of the measurement circuit is shown in Figure 1.

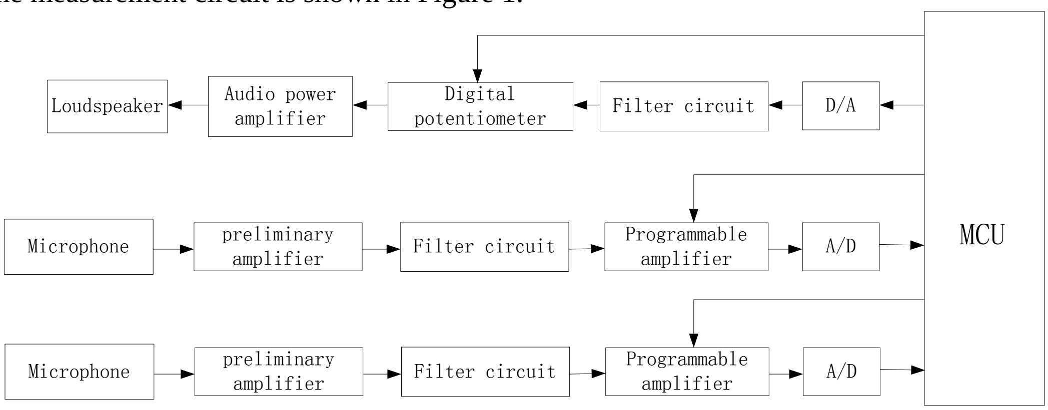


Figure 1. The Diagram of the Measurement Circuit

The circuit consists of two measurement channels and one channel of generating Acoustic stimulation .In the channel of generating acoustic stimulation, D/A converter converts the dual-frequency stimulation signal through digital synthesis to an analog signal, after passing the filter circuits, the digital potentiometer adjusts stimulation intensity, and after passing the audio power amplifier, the analog signal is converted into acoustic stimulation by the loudspeaker. The measurement channels extracts the sound of microphone, turning it into electrical signals, after passing the preamplifier and filter, the signal is amplified by the programmable amplifiers, then put the amplitude signal into the A/D converter. Finally we can get the original measurement data which can be used for building the model.

4. POAE Characteristic Model Based on Volterra Kernel

4.1. The Extraction Method of Volterra Kernel

We can take the ear as a nonlinear system and use the Volterra kernel to describe it. DPOAE is a kind of non-linear steady-state response of the ear to dual-frequency stimulation. This response includes the responses which Volterra kernel generate in each stage and the overall response is the result of interaction of kernels of different stages. Therefore, in order to determine the frequency domain kernel for each stage Volterra kernel of the ear model, the response generated by each stage Volterra kernel need to be separated from the overall response, which can be achieved according to the homogeneity of Volterra kernel [10-12].

We assume that the input value is x (t), and the response can be expressed as

$$y'(t) = \sum_{n=1}^{\infty} y_n(t) \tag{1}$$

Where yn (t) represents a response generated by n-order Volterra kernel, and it can be expressed as

$$y_n(t) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\cdots\int_{-\infty}^{\infty} h_n(\tau_1,\tau_2,\cdots,\tau_n)\prod_{i=1}^{n}[x(t-\tau_i)]\mathrm{d}\tau_1\mathrm{d}\tau_2\cdots\mathrm{d}\tau_n \tag{2}$$

Where hn(τ1,τ2,…,τn) represents the time domain kernel for n-order Volterra, it can also be called as the Generalized impulse response function (GIRF) .
Make an n-dimensional Fourier transform on formula 2, we have

$$Y_n(S_1,S_2,\cdots,S_n) = H_n(S_1,S_2,\cdots,S_n)\prod_{i=1}^{n} X(S_i) \tag{3}$$

Where

$$H_n(S_1,S_2,\cdots,S_n) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\cdots\int_{-\infty}^{\infty} h_n(\tau_1,\tau_2,\cdots,\tau_n)\cdot\exp\left(\sum_{i=1}^{n} S_i\tau_i\right)\mathrm{d}\tau_1\mathrm{d}\tau_2\cdots\mathrm{d}\tau_n$$

Yn(S1,S2,…,Sn) is an n-order output transformation of the system. Hn(S1,S2,…,Sn) is the n-order transform function, or it can be called the Generalized frequency response function (GFRF).

According to the n order homogeneity of Volterra kernel, when we set the input value as ax (t), the response is

$$y'(t) = ay_1(t) + a^2 y_2(t) + \cdots + a^n y_n(t) + \cdots$$

Accordingly, we can determine GFRF by multiplying measurement of different amplitude signals. When the nonlinear degree is low, in other words, its high-order kernel attenuates quickly; the system can be represented approximately by n-th kernel. For example, if N=3, in order to facilitate the solution, we use the input signal which only changes the amplitude. We assume that the three non-zero input signals have same wave form and different amplitude, which can be denoted as a1x (t), a2x (t) and a3x (t). The corresponding output can be denoted as y'1(t), y'2(t) and y'3(t). Then the formula can be denoted as:

$$\begin{cases} y_1'(t) = a_1 y_1(t) + a_1^2 y_2(t) + a_1^3 y_3(t) + e_1(t) \\ y_2'(t) = a_2 y_1(t) + a_2^2 y_2(t) + a_2^3 y_3(t) + e_2(t) \\ y_3'(t) = a_3 y_1(t) + a_3^2 y_2(t) + a_3^3 y_3(t) + e_3(t) \end{cases} \tag{4}$$

Where ei (t) (i=1, 2, 3) are measurement errors and forth-and higher-order truncation errors. The matrix form can be denoted as:

$$\begin{bmatrix} y_1'(t) \\ y_2'(t) \\ y_3'(t) \end{bmatrix} = \begin{bmatrix} a_1 & a_1^2 & a_1^3 \\ a_2 & a_2^2 & a_2^3 \\ a_3 & a_3^2 & a_3^3 \end{bmatrix} \begin{bmatrix} y_1(t) \\ y_2(t) \\ y_3(t) \end{bmatrix} + \begin{bmatrix} e_1(t) \\ e_2(t) \\ e_3(t) \end{bmatrix} \tag{5}$$

On the assumption that the system is weakly nonlinear, its high-order kernels attenuate very quickly, so

ei(t) = 0 (i=1,2,3)

Each order can be obtained to produce kernels response y (t). This method of isolating the response of kernels of each order from the overall response is called the Vandermode method [13]. The Idea of Frequency-domain kernel measurements are the same as the method mentioned above. After obtaining the yn (t), the frequency-domain kernel can be represented as:

$$H_n(s_1, s_2, \dots, s_n) = Y_n(s_1, s_2, \dots, s_n) \Big/ \prod_{i=1}^{n} U(s_i) \tag{6}$$

In order to reduce the impact of measurement error, this paper increases the number of measurement, gets a set of overdetermined equations, and uses the least squares method to solve the equations and reduce the errors.

4.2. Experimental Data Acquisition

The sensor designed in this study is to measure background sounds. In order to simplify the modeling process, we ignore the background sound effects first; the noise reduction outcome will be published sequentially. Therefore, the experimental data is acquired with noise reduction headset. However, since the experiment took place in a common school laboratory, the interference cannot be completely excluded.

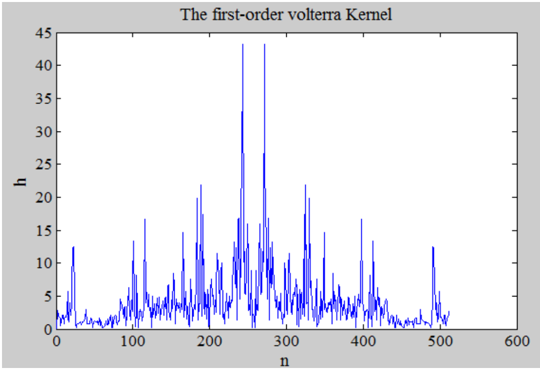
According to the principle of Vandermode, the measurement data of sound stimulation and otoacoustic emissions is required. We use 100ms pure tone pulse for DPOAE measurement, because DPOAE occured within a few millimeters after inducing stimulus, therefore, the two signals mix together. In order to separate them, we use the two-step method for the measurement of different intensity and frequency [14]. First, fix the sensor that can produce and receive sound signals on the emulational ear, and seal it in a little box with a sound-absorbing layer to measure stimulus separately, then measure the mixed sound by putting the detector into the ear.

We use dual-tone signal of 1 kHz and 1.22 kHz as stimulus, and test the subjects using three different intensity, 3 times for each intensity, sampling frequency is 20 kHz with 512 continuous sampling points. Then we repeat the test on the same subjects after a week and another test after another week and record the data of the 22 subjects for the 3 times. These data are used for modeling, testing the stability of the characteristic and identity identification experiment.

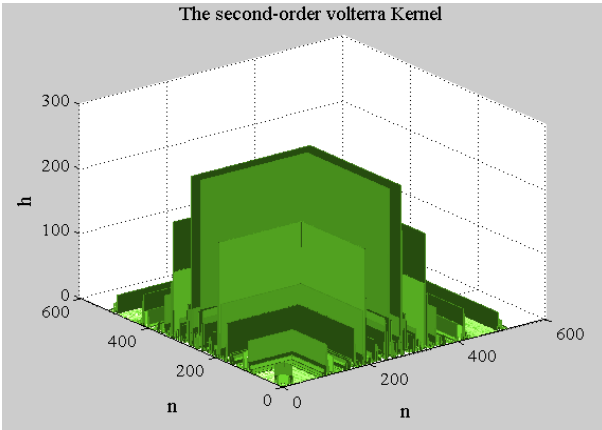
4.3. DPOAE Feature Modeling of Ear

According to formula (5), using the 512 data points of the 9 groups from the three intensity, the nine overdetermined equations which include three variables of y1(t),y2(t),y3(t) can be established and solved by means of the least squares method. Then, combined with the formula (6), the Volterra frequency kernels can be obtained.

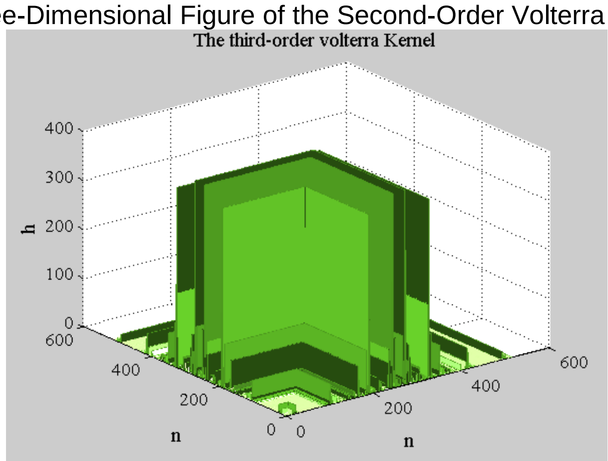
According to the degree of nonlinearity and application needs, more multi-order kernels should be solved; this article only uses the first 3 order kernels as an example [15-16]. Take one of the subject's data for example, the solved Volterra frequency kernels of the first-order, second-order and third-order are shown in Figure 2.



a. The First-Order Volterra Kernel



b. The Three-Dimensional Figure of the Second-Order Volterra Kernel



c. The Three-Dimensional Figure of the Third-Order Volterra Kernel

Figure 2. Figure of the different Order of the Volterra Kernel

Figure 2.c is drawn on the condition that one variable is viewed as constant. In order to observe conveniently, make the variables s1=s2=s3, therefore the second and third order of the Volterra kernel can be represented by two-dimensional figure which is a cutaway view of them.

To note that, the Volterra frequency domain kernel above is represented by the matrix with 512 data points, with the help of the curve fitting function of the MATLAB simulation software, the unary function of the different-order Volterra kernels are obtained.

The first-order Volterra kernel:

H1(s) = a1*exp (-((s-b1)/c1)2) + a2*exp (-((s-b2)/c2) 2) +a3*exp (-((s-b3)/c3) 2) + a4*exp (-((s-b4)/c4) 2) +a5*exp (-((s-b5)/c5) 2) + a6*exp (-((s-b6)/c6) 2) (7)

Among them, a1=38.71, b1 = 271.2, c1= 0.8959, a2 =38.69, b2=242.8, c2=0.8886, a3=8.448, b3=324.5, c3=1.504, a4 =28.44, b4 =188.8, c4 =0.2518, a5 =11.8, b5 =72.22, c5 =291, a6 =-9.951, b6 =57.49, c6 =150.4。 The fitted R-square=0.5124, RMSE=3.324。 The first-order kernel fitting comparison as shown in Figure 3.

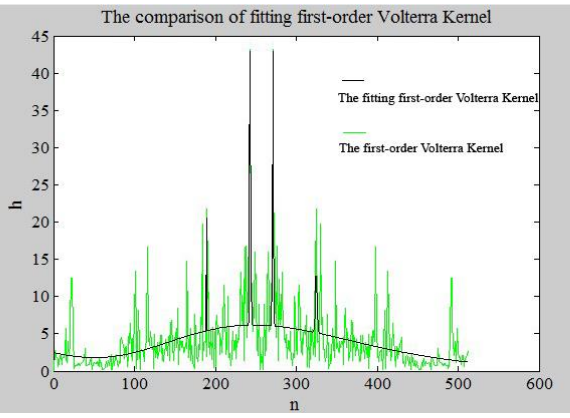


Figure 3. First-Order Kernel Profile Fitting Comparison Chart

The second-order Volterra kernel(s=s1=s2):

H2(S) =a1*exp (-((s-b1)/c1)4) +a2*exp (-((s-b2)/c2)4) + a3*exp (-((s-b3)/c3)4) + a4*exp (-((s-b4)/c4)4) + a5*exp (-((s-b5)/c5)4) + a6*exp (-((s-b6)/c6)4) (8)

Among them,a1=274.2, b1=271.2, c1=0.607, a2=274.4, b2=242.8, c2=0.6059, a3=169.3, b3=325, c3=0.3045, a4 =168.1, b4=189, c4=0.2548, a5=30.41, b5=198.6, c5=140.1, a6=-20.62, b6=156.8, c6=111.4, the fitted R-square=0.7355, RMSE=12.36。 The second-order kernel fitting comparison as shown in Figure 4.

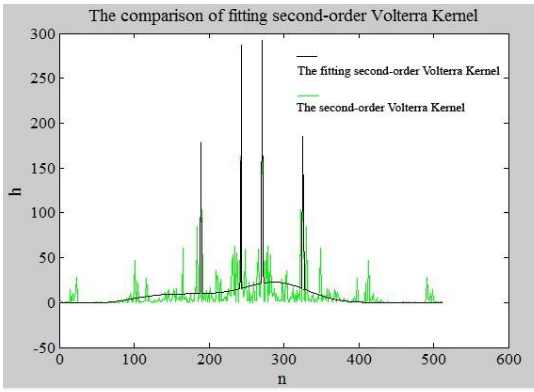


Figure 4. Second-Order Kernel Profile Fitting Comparison Chart

The third-order Volterra kernel (s=s1=s2=s3):

H3(S) =a1*exp (-((s-b1)/c1)6) + a2*exp (-((s-b2)/c2)6) + a3*exp (-((s-b3)/c3)6) + a4*exp (-((s-b4)/c4)6) + a5*exp (-((s-b5)/c5)6) + a6*exp (-((s-b6)/c6)6) + a7*exp (-((s-b7)/c7)6) + a8*exp (-((s-b8)/c8)6) (9)

Among them, a1=411.1, b1=271.1, c1=0.5828, a2=411.1, b2=242.9, c2=0.5828, a3=397.2, b3=325.1, c3=0.3955, a4=396.7, b4=188.9, c4=0.3959, a5=34.03, b5=280.2, c5=5.403, a6=34.03, b6=233.8, c6=5.403, a7=103.5, b7=265.9, c7=0.6416, a8=103.5, b8=248.1, c8=0.6416, the fitted R-square=0.8575,RMSE=14.21。The third-order kernel fitting comparison as shown in Figure 5.

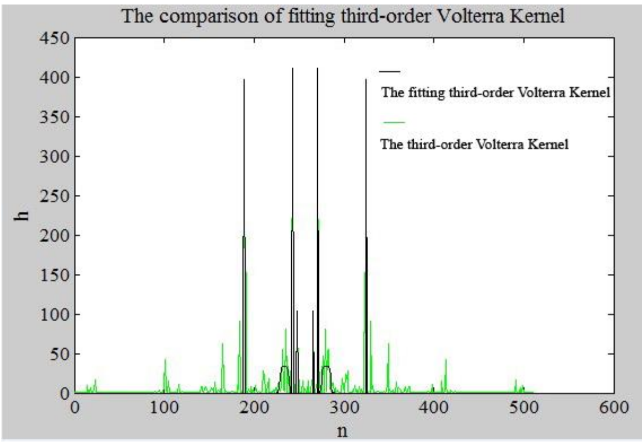


Figure 5. Third-Order Kernel Profile Fitting Comparison Chart

4.4. Based on Intelligent Feature Extraction and BP Neural Network of Biometric Identification Experiments and Results

In order to verify the feasibility of applying the model of biometric identification, we conducted two experiments, one on the difference in DPOAE characteristics of different ears and another on the stability of DPOAE characteristics.

According to the methods described, we can build model using the acquired data (66 data from 22 subjects), using improved annealing genetic algorithm for intelligent extracting of ear feature model DPOAE [17]. The approach extracts 3 characteristics of per-order kernel, a total of 9 characteristics of 3-order kernels, and constitutes a feature vector according to certain rules. Design a BP neural network with 9 input, 5 output nodes, 3-tier architecture, and output with encoding to identify individuals [18]. Use the characteristics of the 22 people in the first test as sample to train the BP neural network. Set the root-mean-square error of the network between actual output and expected output to be less than 0.001. After a successful training, put the remaining 44 samples model of the feature vector into BP neural networks for identification, the successful identification rate is 100% percent.

5. Conclusions

In this paper, we built human ear's DPOAE feature model based on Volterra frequency kernel, used improved stimulation annealing genetic mixed algorithm to extract the feature of human ear's DPOAE feature model intelligently. With limited testing samples, the successful recognition rate can reach 100%. It laid the foundation for using DPOAE for biological information identification.

During the research process mentioned above, due to limited sample, we ignored the effects of environmental noise, and the function fitting effect also needs to be improved. We will continue the research in this area in the future, such as researching on the transfer model of environmental noise outside the ear to the inner ear, noise elimination methods and comparing with other DPOAE feature's modeling methods.

Acknowledgements

This study obtained support from the National Natural Science Foundation of China and Harbin Science and Technology Bureau（China）, with project number being 61179024 and 2014DB1AG021 respectively, thanks very much! Thanks to all hard working members in the research group! Meanwhile thanks to all the graduate students who participated in the test! Thanks to peers who exchanged academic knowledge and the references' authors since your scientific and technological achievements gave us a lot of help!

References

[1] S. Aleksandra, P. Lucyna and G. Wojciech, "DPOAE in estimation of the function of the cochlea in tinnitus patients with normal hearing", Auris Nasus Larynx, vol.37, no.1, **(2010)**, pp. 55-60.

[2] J. H. Jun, G. Qin and C. Shixiong. "Determination of window duration in time-domain decomposition algorithms for DPOAE", J Tsinghua Univ. (Sci. & Tech.), vol. 48, no.9, **(2008)**, pp. 1515-1518.

[3] D. J. Hecker, J. Lohscheller and C. A. Bader, "A New Method to Analyze Distortion Product Otoacoustic Emissions (DPOAEs) in the High-Frequency Range Up to 18 kHz Using Windowed Periodograms", IEEE Transactions on Biomedical Engineering, vol. 58, no. 8, August **(2011)**, pp. 2369-2375.

[4] D. McFadden, A. G. Sierra and M. D. Hsieh. "Relationships between otoacoustic emissions and a proxy measure of cochlear length derived from the auditory brainstem response", Hear Res., vol. 289, no. 1-2, July **(2012)**, pp. 63–73.

[5] Parazzini, M., Hall, A. J., Lutman, M. E. and Kapadia S., "Effect of aspirin on phase gradient of 2F1–F2 distortion product otoacoustic emissions", Hearing Research, vol. 205, no. 1-2, **(2005)**, pp. 44-52.

[6] Y. Liu and L. Xie, "The intensity of Stimulus effects on hearing distortion product otoacoustic emissions in normal young people", Journal of Audiology and speech pathology, vol. 14, no. 2, **(2006)**, pp. 137-139.

[7] H. Wang and F. Zhou, "Effects of f2/f1 frequency ratio on distortion product otoacoustic emissions", Chinese Journal of Otology, vol. 1, no.1, **(2003)**, pp. 41-42.

[8] C. Abdala and S. Dhar, "Distortion product otoacoustic emission phase and component", Journal of the Acoustical Society of America, vol. 127, no. 1, **(2010)**, pp. 316-325.

[9] Thornton A. R., Lineton B. and Baker V. J., "Nonlinear properties of otoacoustic emissions in normal and impair-ed hearing", Hearing Research, vol. 219, no. 1-2, **(2006)**, pp. 56-65.

[10] Y. Haiying, W. Tieliul and C. Guangju, "Fault diagnosis method in nonlinear analog circuit based on Volterra frequency--domain kernel and neural network", Chinese Journal of Scientific Instrument, vol. 28, no.5, **(2007)**, pp. 807-810.

[11] L. Sang, J. Wang, Y. Xu and R. Xu, "Extracting Volterra series representation from X-parameters for the modeling of microwave device", Journal of Electromagnetic Waves and Applications, vol. 27, no. 3, **(2013)**, pp. 299-308.

[12] X. He and W. M. Ni, "The effects of diffusion and spatial variation in Lotka-Volterra competition-diffusion system I: Heterogeneity vs. homogeneity", Journal of Differential Equations, vol. 254, no.2, **(2013)**, pp. 528-546.

[13] Jiao L. C., "Theory and application of nonlinear transfer function", XiDian university press, vol. 5, **(1992)**.

[14] H. Haitao, M. Hongguan and Y. Ningyu, "Method of Identifying Volterra Frequency-Domain Kernels Based on Stimulus of Multi-tone Signal", Journal of Southwest Jia07rong University, vol. 48, no. 2, April **(2013)**, pp. 250-255.

[15] Kibangou A. Y. and Favier G., "Identification of Parallel-Cascade Wiener Systems Using Joint Diagonalization of Third-Order Volterra Kernel Slices", IEEE Signal Processing Letters, vol. 16, no. 1-3, **(2009)**, pp. 188-191.

[16] Soni A. S. and Parker R. S., "Tailored sequence design for third-order Volterra model identification", Industrial and Engineering Chemistry Research, vol. 46, no.3, **(2007)**, pp. 818-829.

[17] H. Lin, L. Y. Zhang and D. Y. Ren, "Fault diagnosis in nonlinear analog circuit based on Wiener kernel and BP neural network", Chinese Journal of Scientific Instrument, vol. 30, no. 9, **(2009)**, pp. 1946-1949.

[18] H. J. Lin, L. Qi and L. Zhang, "Research for analogous circuit fault diagnosis based on BP Neural Network", Electrical Measurement & Instrumentation, vol. 44, no. 504, **(2007)**, pp. 41-43, 51.

[19] S. N. Han, H. W. Yao, J. Y. Fang and H. Li, "Fingerprint Image Division and Enhancement Algorithm Research", Journal of Harbin University of Science and Technology, vol. 16, no. 1, **(2011)**, pp. 98-101.

