

바이스펙트럼을 이용한 차량의 음향식별

Identification of Acoustic Signals of Vehicles Using Bispectrum

安 鍾 久*, 李 東 珉*, 李 泰 鎬*

(Chong Koo An*, Dong Min Lee*, Tai Ho Lee*)

요 약

어느 신호의 특성을 주파수 영역에서 해석할 때, 파워스펙트럼은 해석하고자 하는 신호의 위상에 관한 정보를 모두 잃어버리는 단점이 있어서, 위상에 관한 정보를 필요로 하는 경우에는 파워스펙트럼 해석법은 그 이용에 제한을 받는다. 고차 스펙트럼(특히 본 논문에서는 3차 스펙트럼인 바이스펙트럼)은 그 계산에 시간이 많이 걸리는 단점은 있으나 반면에 위상에 관한 정보를 잃지 않는다는 장점이 있다. 본 논문에서는 몇가지 이상적인 경우에 대한 바이스펙트럼의 예쁜 보이고, 실제로 노상에서 녹음된 자동차들의 엔진 소음에 대한 바이스펙트럼을 구한후, 이를 이용하여 음향 식별을 할 수 있음을 보였다.

ABSTRACT

Since power spectrum has no information about the phase of a signal, the power spectral analysis technique can not be used to interpret the phase coherency of the signal produced by some nonlinear process. In this case, the third-order spectrum, the so called bispectrum, is very useful in analyzing such signals. Some typical computer simulation results are shown in order to represent the usefulness of the bispectrum, and the bispectra of the measured acoustic signals of three vehicles are shown in order to use to identify the sources of those signals.

1. Introduction

Conventional power spectral analysis technique, which is based on autoand cross power spectrum, has been a very useful tool to analyze practical random signals in many fields of science and engineering. However, it is of limited value when analyzing various spectral components, which interact with one another due to some

nonlinear process since the power spectrum has no information about the phase of the random signals. The phase coherence existing between two (quadratically) nonlinearly interacting spectral components and a resultant sum (or difference) spectral component may be detected with the aid of the third order spectrum, the so called bispectrum.

Let us consider, for example, three spectral components of which the frequencies are ω_1 , ω_2 and $\omega_3 = \omega_1 + \omega_2$ in a random signal. If the three spectral components are independently excited,

*Department of Electronic Engineering Ulsan University
접수일자: 1991. 8. 28.

the phases of the three spectral components are random and independent of one another, and, thus, in this case the three spectral components are not coupled. On the other hand, if the spectral components at ω_1 and ω_2 interact to form a third spectral component at $\omega_3 = \omega_1 + \omega_2$ due to a quadratic interaction, then a phase coherence will exist between three spectral components at ω_1 , ω_2 , and ω_3 . In other words the spectral components at ω_1 , ω_2 , and ω_3 become coupled or correlated. Obviously, classical auto-power spectra are of no value in detecting such phase coherence because all phase information is lost in estimating auto-power spectra, in other words, we can not discriminate the above two cases by using the auto-power spectra since the power spectra of the above two cases are not different. However, due to the sensitivity of the bispectrum to the phase coherence, that is, the correlation between such three spectral components in the random signal, we can discriminate the above two cases by using the bispectra.

The bispectrum has been applied to many areas of science and engineering to analyze and interpret data associated with quadratically nonlinear phenomena. Many of these applications have been mentioned in the review paper by C.L. Nikias and M.R. Raghuveer^[11]. The bispectrum and fourth order cumulant methods have been used in order to estimate time delays in the underwater acoustics signal processing area^[12,3] and the advantages of the phase recovery from bispectra has been studied in^[4]. The bispectrum has been applied to studies of ocean waves by Elgar and Guza^[5] and Kim and Dalzell^[6] used bispectral analysis techniques to model the nonlinear response of ships to sea waves. Powers and his colleagues have exploited the properties of the bispectrum to study three-wave coupling phenomena in plasmas^[7], fluids^[8] and oscillations of moored vessels in a random sea^[9].

Bispectral techniques have also been applied to analyze the radar signature by Walton and Jouny^[10], to determine the optical transfer function by Barakat and Ebstein^[11], to detect holographic information by Sato and Sasaki^[12], to analyze speech signals by Wells^[13]. On the other hand, bispectral windows are studied in^[14], an optimized parametric method to estimate of the bispectrum is studied in^[15] and a parallel processing technique of the bispectrum for the biomedical signal processing is studied in^[16].

In the next section, some properties of the bispectrum will be described. In Section, III, the bispectra of some typical examples which represent the usefulness of the bispectrum are shown. In Section IV, the bispectra of three vehicles, that is, a car with a small gasoline engine, a bus with a large diesel engine, and a small truck with a small diesel engine, will be shown. Conclusion with the future work will be given in the last section, Section V.

II. Properties of Bispectrum

Consider a real zero-mean random process $x(t)$, then the triple correlation function, namely bico-relation function, of the random process is defined by

$$R_{xxx}(\tau_1, \tau_2) = E[x(t)x(t-\tau_1)x(t-\tau_2)] \quad (1)$$

where E denotes the expected value. As shown in Eq.(1), the bico-relation function is a function of two time delays, τ_1 and τ_2 . The symmetry properties of the bico-relation function is easily derived from Eq.(1),

$$\begin{aligned} R_{xxx}(\tau_1, \tau_2) &= R_{xxx}(\tau_2, \tau_1) = R_{xxx}(-\tau_1, -\tau_2) \\ &= R_{xxx}(\tau_2, -\tau_1) \end{aligned} \quad (2)$$

As the correlation function is the 1-D inverse

Fourier transform of the power spectrum, the bicoherence function can be defined by the 2-D inverse Fourier transform of the bispectrum, $S_{xxx}(f_1, f_2)$,

$$R_{xxx}(\tau_1, \tau_2) = \int_{-\frac{f_s}{2}}^{\frac{f_s}{2}} \int_{-\frac{f_s}{2}}^{\frac{f_s}{2}} S_{xxx}(f_1, f_2) e^{i2\pi(f_1\tau_1 + f_2\tau_2)} df_1 df_2 \quad (3)$$

On the other hand, the bispectrum can be defined in the frequency domain as follows :

$$E[X(f_0)X^*(f_1)X^*(f_2)] = S_{xxx}(f_1, f_2) \delta(f_0 - f_1 - f_2) \quad (4)$$

where $X(f)$ is 1-D Fourier transform of $x(t)$ and $*$ stands for the complex conjugate. The symmetry properties of the bispectrum are given as follows :

$$\begin{aligned} S_{xxx}(f_1, f_2) &= S_{xxx}(f_2, f_1) = S_{xxx}(f_1, -f_2) \\ &= S_{xxx}^*(-f_2, -f_1) = S_{xxx}^*(f_1 + f_2, -f_2) \end{aligned} \quad (5)$$

Since our objective is to evaluate the bispectrum digitally, we require, in order to satisfy the sampling theorem, that not only $f_1 \leq \frac{f_s}{2}$, $f_2 \leq \frac{f_s}{2}$, but also $f_1 f_2 \leq \frac{f_s}{2}$, where f_s is the sampling frequency. Thus, as a result of the symmetry properties and the constraints of the sampling theorem, it is necessary to only compute the auto-bispectrum within the triangular region defined by the lines $f_2=0$, $f_2=f_1$ and $f_1+f_2=\frac{f_s}{2}$, that is, Region 1 in Fig.1. In other words, we evaluate the bispectrum of the Region 1, then we can easily obtain the bispectra of the other 11 regions(i.e., Region 2 to Region 12). The explanation about the shaded square area in Fig 1 will be given in Section IV.

III. Bispectra of the Generated Signals

Consider the signal given by

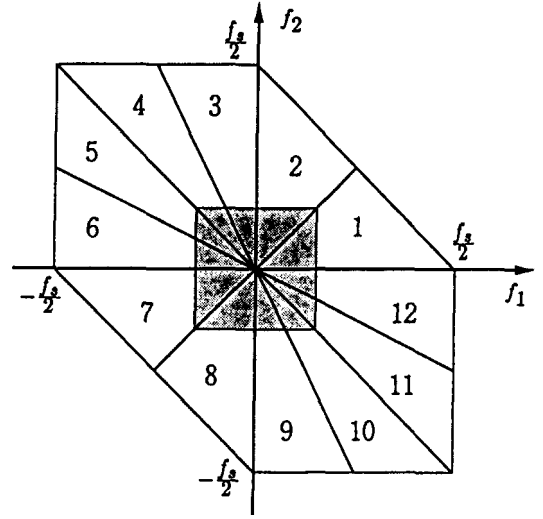


Fig. 1. Two dimensional frequency domain in which auto-bispectra are defined.

$$\begin{aligned} x(t) &= \sqrt{2} [\cos(2\pi g_1 t + \theta_1) + \cos(2\pi g_2 t + \theta_2) \\ &+ \frac{1}{2} \cos(2\pi g_3 t + \theta_3) + \cos(2\pi g_4 t + \theta_4) \\ &+ \cos(2\pi g_5 t + \theta_5) + \frac{1}{2} \cos(2\pi g_6 t + \theta_6)] \end{aligned} \quad (6)$$

where $g_1=38Hz$, $g_2=30Hz$, $g_3=68Hz$, $g_4=74Hz$, $g_5=12Hz$ and $g_6=86Hz$, and $\theta_1+\theta_2=\theta_3$ and $\theta_4+\theta_5 \neq \theta_6$, that is, the former three sinusoids are fully correlated (because of their phase coherence), but the latter three sinusoids are uncorrelated(no phase coherence). The sampling frequency is $256Hz$ (that is, the Nyquist sampling rate), the number of realization (M) is 64 and the number of data points in each realization (N) is 128, (that is, 128-point FFT is used), and thus the total number of data points is 8k(i.e., 8912). This experiment is carried out without noise in order to show the bispectrum of an ideal case.

The amplitudes of the power spectral components at g_1 , g_2 , g_3 and g_4 are 1.0 and those of the power spectral components at g_5 and g_6 are 0.25, as shown in Fig.2(a). In Fig.2(a), we can not find any differences between the coupling relationship among the sinusoids of which the frequencies are g_1 , g_2 and g_3 and that

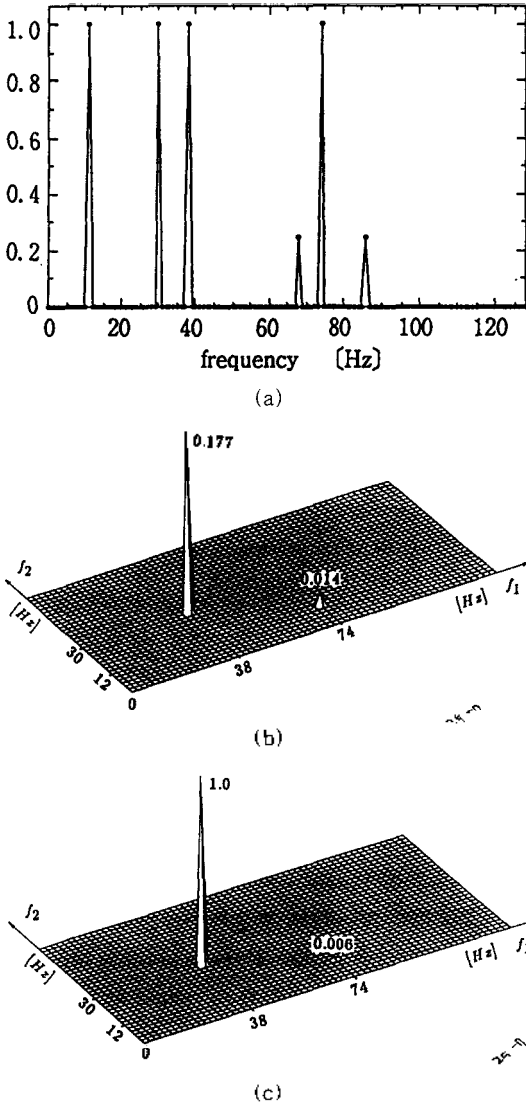


Fig. 2. Coupled and noncoupled sinusoids shown in Eq. (8): (a)power spectrum, (b)bispectrum, (c) bicoherence spectrum.

among the sinusoids of which the frequencies are g_1 , g_5 and g_6 .

However, if we estimate the bispectrum of sinusoids, we can detect the differences as shown in Fig.2(b). In Fig.2(b), the amplitude of the bispectral component at (38Hz, 30Hz) is 0.177 and that of the bispectral component at (74Hz, 12Hz) is 0.014. Ideally, the latter must be zero if the phases of the three sinusoids of which the frequencies g_1 , g_5 and g_6 (i.e., θ_1 , θ_5 and θ_6) are

completely random. However, since the uniformly distributed random numbers generated by the computer, which are used to calculate the phases of the sinusoids, are not completely random, the amplitude of the bispectral component at (74Hz, 12Hz) is not zero but a small value.

The bicoherence spectrum is a measure of degree of the coupling (in this paper, the quadratic nonlinearity) of three sinusoids. The maximum value of the bicoherence spectrum is 1.0 and the minimum value is zero. The bicoherence spectrum is shown in Fig.2(c). The amplitude of the bicoherence spectral component at (38Hz, 30Hz) is 1.0, that is, three sinusoids of which the frequencies are g_1 , g_2 and $g_3(=g_1+g_2)$ are completely coupled, and that of the bicoherence spectral component at (74Hz, 12Hz) is 0.006 (i.e., nearly zero), that is, three sinusoids of which the frequencies are g_1 , g_5 and $g_6(=g_1+g_5)$ are not coupled.

Next, we consider another test signal such that

$$\begin{aligned}
 x(t) = & \sqrt{2} [\cos(2\pi g_1 t + \theta_1) + \cos(2\pi g_2 t + \theta_2) \\
 & + \cos(2\pi g_3 t + \theta_3) \cos(2\pi g_4 t + \theta_4) \\
 & + \frac{1}{2} \cos(2\pi g_5 t + \theta_5)] \quad (7)
 \end{aligned}$$

where $g_1=52\text{Hz}$, $g_2=34\text{Hz}$, $g_3=86\text{Hz}$, and θ_1 , θ_2 and θ_3 are random, that is, $\theta_1 + \theta_2 \neq \theta_3$. The sampling frequency is also 256Hz, the number of realizations is 64 and each realization contains 128 data points.

The power spectrum of the signal is shown in Fig.3(a). The amplitudes of the power spectral components at g_1 and g_2 are 1.0, that of the power spectral component at g_1+g_2 (i.e., 86Hz) is 0.510 and that of the power spectral component at g_1-g_2 (i.e., 18Hz) is 0.250. All power of the 18Hz sinusoid comes from the coupling of two sinusoids, $\cos(2\pi g_1 t + \theta_1)$ and $\cos(2\pi g_2 t + \theta_2)$. However, half of the power of the 86Hz sinusoid

comes from the coupling of two sinusoids, $\cos(2\pi g_b t + \theta_b)$ and $\cos(2\pi g_c t + \theta_c)$, but the other half of the power of the 86Hz sinusoid comes from the noncoupled sinusoid $\frac{1}{2} \cos(2\pi g_d t + \theta_d)$. In practical situation, the noncoupled sinusoid $\frac{1}{2} \cos(2\pi g_d t + \theta_d)$ could be considered as a random noise.

The bispectrum and the bicoherence spectrum of the signal expressed by Eq.(7) are shown in Fig.3(b) and (c), respectively. In Fig.3(b), the amplitude of the bispectral component at (34Hz

18Hz) is 0.177 and that of the bispectral component at (52Hz 34Hz) is 0.181. Since the uniformly distributed random numbers generated by the computer, which are used to calculate the phases of the sinusoids, are not completely random, both amplitudes of the bispectra are slightly different. The amplitude of the bicoherence spectral component at (34Hz 18Hz) is 1.0 which implies that three sinusoids of which the frequencies are g_b , g_c and $g_d (=g_b - g_c)$ are completely coupled, and that of the bicoherence spectral component at (52Hz, 34Hz) is 0.516 which implies that only half of the power of the sinusoid of which the frequency is $g_d (=g_b + g_c)$ is due to the nonlinear interaction between the sinusoids of which the frequencies are g_b , g_c . If three sinusoids of which the frequencies are g_b , g_c and $g_d (=g_b + g_c)$ are fully coupled, the amplitude of the bispectral component at (52Hz, 34Hz) will be doubled, since the amplitude of the power spectral component at g_c (i.e., 86Hz) is 0.510 and that of the power spectral component at g_d (i.e., 18Hz) is 0.250.

IV. Bispectra of Acoustic Signals of Vehicles

Acoustic signals are collected from the three different vehicles, that is, a 5-passenger car with a small gasoline engine, an express bus with a relatively large diesel engine and a 2.5-ton truck with a relatively small diesel engine. When each vehicle, of which the engine runs idle, is stopped on a noisy road, the acoustic signal, precisely speaking, noise, of each vehicle is recorded for 2 seconds about 1m apart from the engine of the vehicle. The sampling frequency is 10kHz since almost all power of each signal lies under 2.0kHz, that is, in this case 10kHz sampling rate is high enough to avoid aliasing. Therefore, the data length of each signal is 20k (i.e., 20480). The power spectra of the acoustic signals of the car,

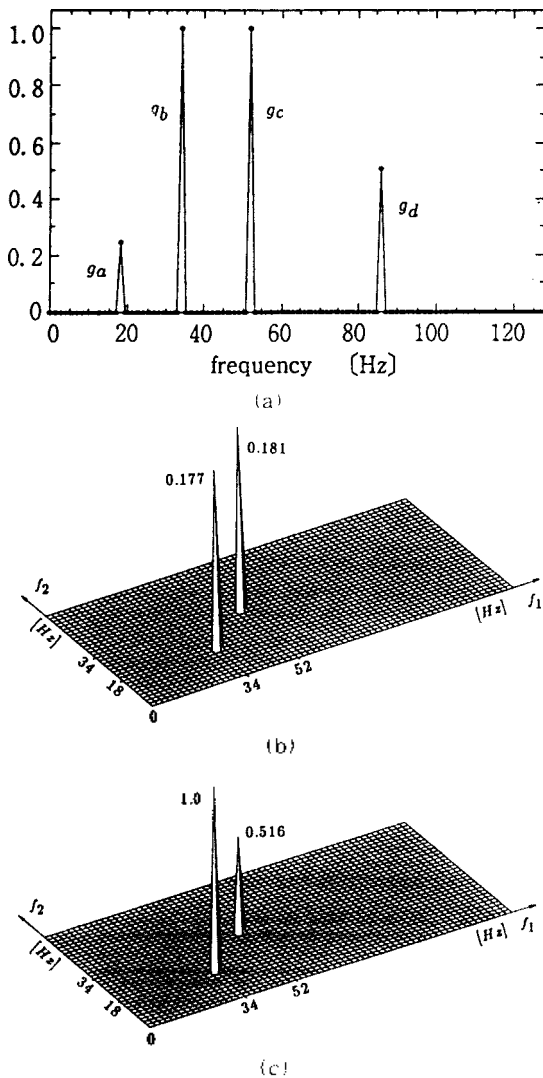
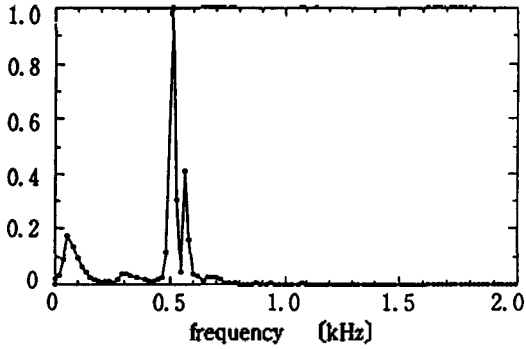
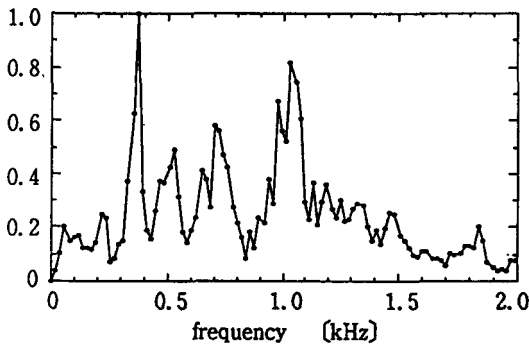


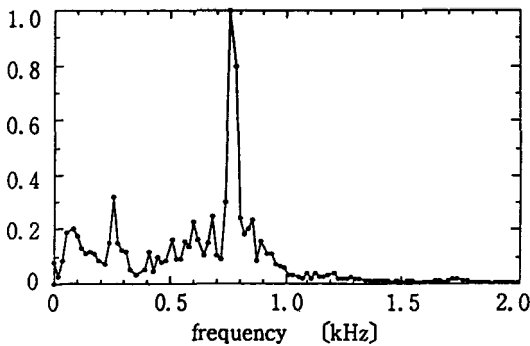
Fig. 3. Partially coupled sinusoids shown in Eq.(7). (a) power spectrum, (b) bispectrum, (c) bicoherence spectrum.



(a)



(b)



(c)

Fig. 4. Power spectra of the acoustic signals : (a)car, (b)bus, (c)truck.

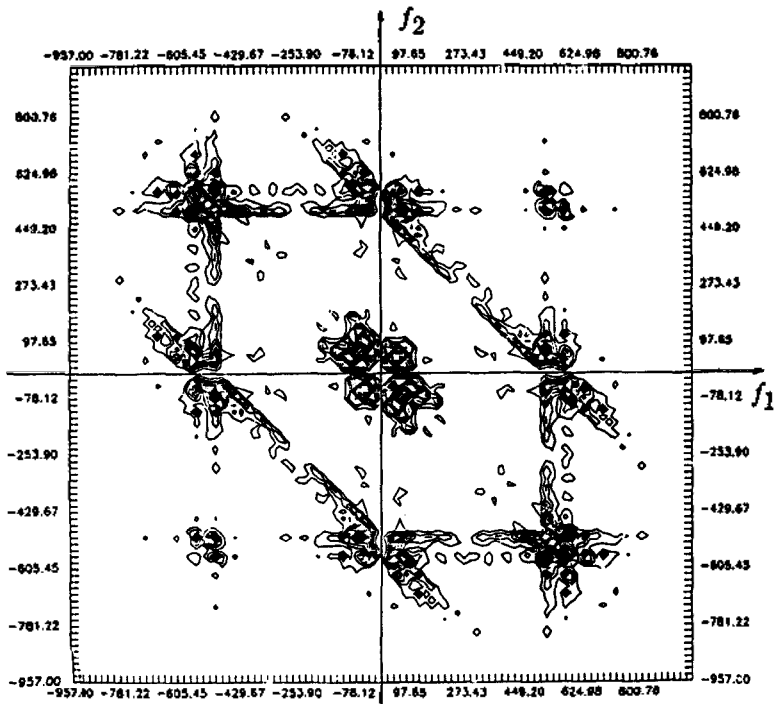
the bus and the truck are shown in Fig.4(a), (b) and (c), respectively. Each spectrum is averaged over 40 realizations and 512-point FFT is used, i. e. each realization consists of 512 data samples for high resolution.

Since the sampling rate is high enough, we need to calculate the bispectrum of the shaded area of the triangular Region 1 in Fig.1. However, we calculate the bispectrum of the 12

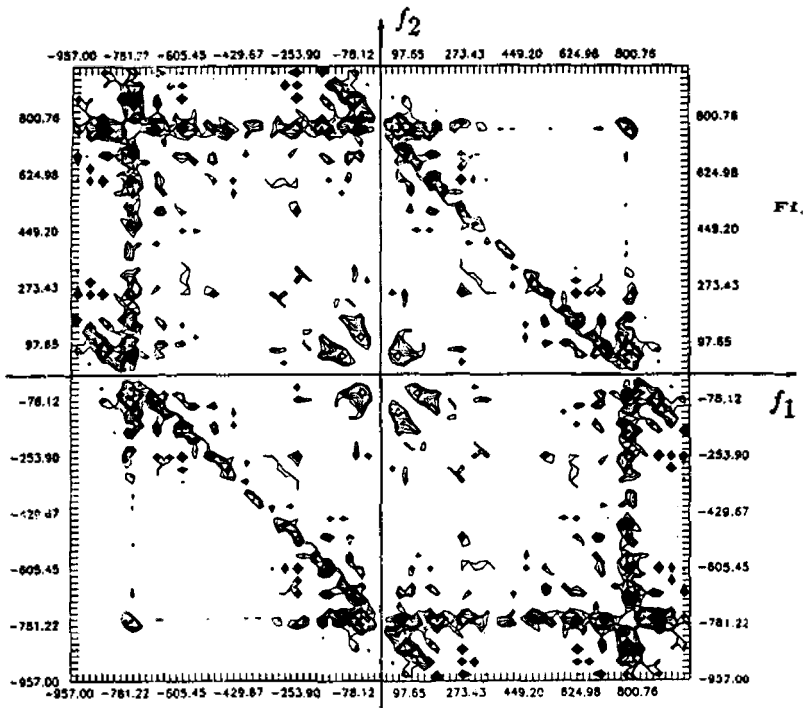
shaded area in order to obtain symmetric bispectrum patterns. The lowest frequency of the shaded area is about -1kHz and the highest frequency is about 1kHz due to the limitation of the software package we have, which can be used to draw, at largest, 10000-point contour plot. The contour plots of the shaded area of the bispectra of the acoustic signals of the car, the bus and the truck are shown in Fig.5(a), (b) and (c), respectively. Although we can identify the sources of the acoustic signals by using the power spectra shown in Fig.4(a), (b) and (c), we can also identify the sources by using the bispectrum patterns shown in Fig.5(a), (b) and (c). However, if we use bispectrum patterns in order to identify the sources of acoustic signals, we can also utilize well-known pattern recognition techniques.

V. Conclusion

As shown in Section III, since both the power spectra of two different signals could be equal, it is not enough, sometimes, to identify the signals by using the power spectrum technique. However, the bispectrum technique is able to identify the two signals, since bispectrum can detect the phase coherence of the signal. Since the contour plot of the bispectrum of a signal looks like a pattern as shown in Section IV, we can apply many pattern recognition techniques in order to identify the sources of signals. Also, it is relatively easy to identify the sources of signals by human eyes. In addition, if we use both the power spectrum technique and the bispectrum technique in order to identify the sources of acoustic signals, the probability of the identification will be higher. Since one of the disadvantages of the bispectrum technique is the fact that the computation time to estimate the bispectrum is longer than that to estimate the power spectrum, the higher order spectra including the bispectrum



(a)



(b)

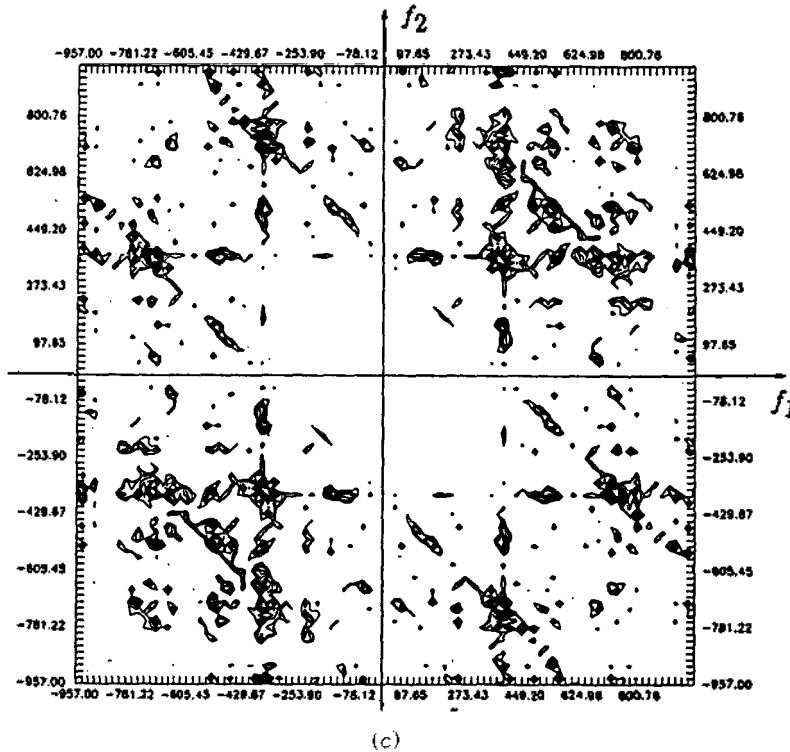


Fig. 5. Bispectra of the acoustic signals : (a)car. (b) bus. (c)truck.

have not been widely utilized. However, the computation time becomes less important due to the appearance of high speed computers.

We prepare the next paper in which we consider the bispectra of the acoustic signals of the vehicles with additive Gaussian noises. After then, we apply neural network techniques to the identification of the source of a signal by using the bispectrum pattern in the future. Ultimately, we are going to apply this technique to the underwater target identification using sonar.

References

1. C.L.Nikias and M.R.Raghuvver, "Bispectrum Estimation: A Digital Signal Processing Framework," *Proc. IEEE*, Vol.75, No.7, pp.869-891, July 1987.
2. H.H.Chiang and C.L.Nikias, "A New Method for Adaptive Time Delay Estimation for Non-Gaussian Signal," *IEEE Trans. Acoustics, Speech and Signal Processing*, Vol.38, No.2, pp.209-219, Feb.1990.
3. J.K.Tugnait, "On Time Delay Estimation with Unknown Spatially Correlated Gaussian Noise Using Fourth-Order Cumulants and Cross Cumulants," *IEEE Trans. Signal Processing*, Vol.39, No.6, pp.1258-1267, June 1991.
4. H.Bartelt, A.W.Lohmann and B.Wirmitzer, "Phase and Amplitude Recovery from Bispectra," *Appl. Opt.*, Vol.23, No.18, pp.3121-3129, Sept.1984.
5. S.Elgar and R.T.Guza, "Observations of Bispectra of Shoaling Surface Gravity Waves," *J. Fluid Mech.*, Vol.161, pp.425-448, 1985.
6. J.F.Dalzell and C.H.Kim, "An Analysis of the Quadratic Frequency Response for Lateral Drifting Force and Moment," *J. of Ship Research*, Vol.23, pp.185-208, 1979.
7. Y.C.Kim and E.J.Powers, "Digital Bispectral Analysis and its Applications to Nonlinear Wave Interactions," *IEEE Trans. Plasma Science*, Vol.18, pp.120-131, June 1979.
8. E.J.Powers and R.W.Milesod, "Polyspectral Measurement and Analysis of Nonlinear Wave

- Interactions," in *Nonlinear Wave Interactions in Fluids*, R.W.Miksad, T.R.Akylos and T.Herbert, editors, American Society of Mechanical Engineers, New York, pp.9-16, 1987. (Book No.G00380).
9. K.I.Kim, E.J.Powers, Ch.P.Ritz, R.W.Miksad and F.J.Fisher, "Modeling of the Nonlinear Drift Oscillations of Moored Vessels Subject to Non Gaussian Random Sea Wave Excitation," *IEEE J. of Oceanic Engineering*, Vol.OE-12, pp.568-575, Oce. 1987.
 10. E.K.Walton and I.Jouny, "Application of Bispectral Techniques to Radar Signature Analysis," Workshop on Higher-Order Spectral Analysis, Vail, Colorado, pp.56-61, June 28-30, 1989.
 11. R.Barakat and S.Ebstein, "Bispectral Diffraction Imagery. I. The Bispectral Optical Transfer Function," *J. Opt Soc. Am.*, Vol.4, No.9, pp.1756-1763, Sept.1987.
 12. T.Sato and K.Sasaki, "Bispectral Holography." *J. Acoust. Soc. Am.*, Vol.62, No.2, pp.404-408, Aug. 1977.
 13. B.Wells, "Voiced /Unvoiced Decision Based on the Bispectrum," *Proc. of ICASSP*, Tampa, Florida, 1589-1592, 1985.
 14. T.S.Rao and M.M.Gabr, *An Introduction to Bispectral Analysis and Bilinear Time Series Models*, Springer Verlag, New York, 1984.
 15. C.K.An, S.B.Kim and E.J.Powers, "Optimized Parametric Bispectrum Estimation," 1988 International Conference on Acoustics, Speech and Signal Processing, New York, pp.2392-2395, April 11-14, 1988.
 16. E.S.Manolakos, H.M.Stellakis and D.H.Brooks, "Parallel Processing for Biomedical Signal Processing—Higher Order Spectral Analysis," *IEEE Computer Magazine*, Vol.24, No.3, pp.33-44, March 1991.



▲Chong Koo An was born on July 7, 1953. He received B. S. degree in electrical engineering from the Seoul National University in 1977, M.S. degree in electronic engineering from the Korea Advanced Institute of Science and Technology in 1979 and Ph.D. degree in electrical and computer engineering from the University of Texas at Austin in 1989. In 1979 he joined the Hyundai Heavy Electric Company. Since 1980 he has been with the department of electronic engineering at the Ulsan University, where he is currently an associate professor. He joined the Electronics Research Center at the University of Texas at Austin, as a research fellow, from 1985 to 1989. His research activities are in the areas of spectrum estimation, time delay estimation, higher-order spectral analysis and speech and sonar signal processing. Dr. An is a member of Eta Kappa Nu.



▲Dong Min Lee was born on September 25, 1967. He received B.S. degree in electronic and computer engineering from the Ulsan University in 1991. At present, he is working towards the M.S. degree in electronic engineering at the Ulsan University. His current research interests include speech and sonar signal processing with neural networks.



▲Tai Ho Lee received B.S. degree in electronic engineering from the Hanyang University in 1966, M.S. degree in electronic engineering from the Seoul National University in 1969 and Ph.D. degree in electronic engineering from the Yonsei University in 1975. From 1969 to 1972, he was with the Korean Institute of Science and Technology as a researcher. Since 1973 he has been with the department of electronic engineering at the Ulsan University, where he is a professor. His research interests are in the area of digital signal processing, speech synthesis and recognition, and neural networks.