Multi-scale Modeling Approach for Detecting Low Observable Targets within Sea Clutter

Jing Hu[1], Jianbo Gao[1], Robert S. Lynch[2], and Genshe Chen[3]
[1]Department of Electrical and Computer Engineering,
University of Florida, Gainesville, FL 32611
jinghu@ufl.edu, gao@ece.ufl.edu
[2]Signal Processing Branch, Naval Undersea Warfare Center,
Newport, RI 02841
LynchRS@Npt.NUWC.Navy.Mil
[3]Intelligent Automation, Inc.
15400 Calhoun Dr. Suite 400 Rockville, MD 20855
gchen@i-a-i.com

Abstract—Sea clutter refers to the radar backscatter from the ocean surface. Accurate modeling of sea clutter and rough sea surface is an important problem in radar signal processing and applications, as it facilitates robust detection of low observable targets within sea clutter, which has significant importance to coastal security, navigation safety and environmental monitoring. Great efforts have been made to model sea clutter. However, the nature of sea clutter is poorly understood and the important problem of target detection within sea clutter remains a tremendous challenge. We propose a systematic, multi-scale approach to model sea clutter. By extensively utilizing available real data, we (1) develop methods to better fit non-stationary and non-Gaussian sea clutter, (2) characterize correlation structure of sea clutter on multiple time scales, and (3) develop accurate and readily implementable methods to detect low observable targets within sea clutter. [1 2]

TABLE OF CONTENTS

1. INTRODUCTION

Sea clutter is the backscattered returns from a patch of an ocean surface illuminated by a radar pulse. The development of suitable models that properly characterize radar clutter processes is critical for designing optimum algorithms for detecting targets within radar clutter as well as for performance evaluation of those detectors. In modern radar systems operating at low grazing angles with high resolution capabilities, sea clutter has often been observed to be highly non-Gaussian [1–5]. Hence, sea clutter modeling is a very challenging problem.

In the past few decades, a lot of efforts have been made to model sea clutter. Roughly, these efforts can be classified into four categories: (i) Distributional analysis of sea clutter; (ii) Analysis of sea clutter using fractal theory; (iii) Analysis of sea clutter using chaos theory; (iv) Modeling of sea clutter using various methods for the purpose of detecting targets within sea clutter. Despite these extensive studies, however, the nature of sea clutter is still poorly understood. For example, whether sea clutter is chaotic or not is still a much debated issue [6–15]. As a result, the important problem of target detection within sea clutter remains a tremendous challenge. In this paper, we show that one major complexity in modeling sea clutter is that sea clutter is highly non-stationary and multi-scaled. We then present a new type of distributional analysis to cope with non-stationarity, and describe a multi-scale analysis method for detecting low observable targets within sea clutter.

2. DATA

Fourteen sea clutter datasets were obtained from a website maintained by Professor Simon Haykin: http://soma.ece.mcmaster.ca/ipix/dartmouth/datasets.html. The measurement was made using the McMaster IPIX radar at Dartmouth, Nova Scotia, Canada. The radar was mounted in a fixed position on land 25-30 m above sea level, with an operating (carrier) frequency of 9.39 GHz (and hence a wavelength of about 3 cm). It was operated at low grazing

1

[2] IEEEAC paper #1201, Final Version, Updated Dec 29, 2007

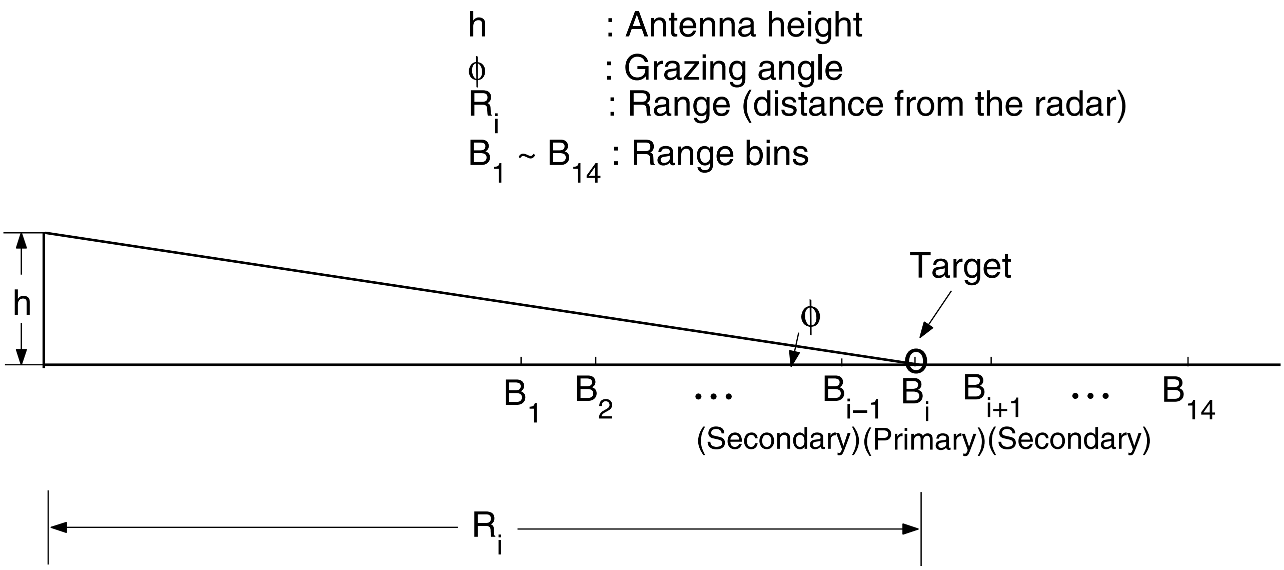


Figure 1 A schematic showing how the sea clutter data were collected.

angles, with the antenna dwelling in a fixed direction, illuminating a patch of ocean surface. The measurements were performed with the wave height in the ocean varying from 0.8 to 3.8 m (with peak heights up to 5.5 m) and the wind conditions varying from still to 60 km/hr (with gusts up to 90 km/hr). For each measurement, 14 areas, called antenna footprints or range bins, were scanned. Their centers are depicted as B_1, B_2, …, B_{14} in Figure 1. The distance between two adjacent range bins was 15m. One or a few range bins hit a target, which was a spherical block of styrofoam of diameter 1 m wrapped with wire mesh. The locations of the three targets were specified by their azimuthal angle and distance to the radar. They were (128^0, 2660 m), (130^0, 5525 m), and (170^0, 2655 m), respectively. The range bin where the target is strongest is labeled as the primary target bin. Due to drift of the target, bins adjacent to the primary target bin may also have hit the target. They are called
secondary target bins. For each range bin, there were 2^{17} complex numbers, sampled with a frequency of 1000 Hz.

3. COMPLEXITIES IN SEA CLUTTER

There are two sources of complexity for sea clutter: the rough sea surface, sometimes oscillatory, sometimes turbulent, and the multipath propagation of the radar backscatter. To be quantitative, in Figure 2, two 0.1 s duration sea clutter signals, sampled with a frequency of 1 KHz, are plotted in (a,b), a 2 s duration signal is plotted in (c), and an even longer signal (about 130 s) is plotted in (d). It is clear that the signal is not purely random, since the waveform can be fairly smooth on short time scales (Figure 2(a)). However, the signal is highly non-stationary, since the frequency of the signal (Figure 2 (a,b)) as well as the randomness of the signal (Figure 2 (c,d)) change over time drastically. Therefore, naive Fourier analysis or deterministic chaos analysis of sea clutter may not be very useful. From Figure 2 (e), where $X_t^{(m)}$ is the non-overlapping running mean of X over block size m and X is the sea clutter amplitude data, it can be further concluded that neither autoregressive (AR) models nor textbook fractal models can describe the data. This is because AR modeling requires exponentially decaying autocorrelation (which amounts to $Var(X_t^{(m)}) \sim m^{-1}$, or a Hurst parameter of 1/2, which will be explained in Sec. 5), while fractal modeling requires the variation between $Var(X_t^{(m)})$ and m to follow a power law. However, neither behavior is observed in Figure 2 (e). Indeed, although extensive work has been done on sea clutter, its nature is still poorly understood. Therefore, in order to effectively detect targets within sea clutter, new multi-scale analysis approaches have to be developed.

4. MODELING SEA CLUTTER AS A NON-STATIONARY AND NON-EXTENSIVE RANDOM PROCESS

It is well-known that sea clutter data are often highly non-Gaussian. There has been much effort to fit various distributions to the observed amplitude data of sea clutter, including Weibull, lognormal, K, and compound-Gaussian distributions [1–5]. However, the fitting of those distributions to real sea clutter data is not excellent and quite often using parameters estimated from those distributions is not very effective for distinguishing sea clutter data with targets from those without targets. Two examples are shown in Figure 3 (c,d) for the fitting using K distribution [3, 8],

$$f(x) = \frac{\sqrt{2v}}{\sqrt{\mu}\Gamma(v)2^{v-1}}\left(\sqrt{\frac{2v}{\mu}}x\right)^{v} K_{v-1}\left(\sqrt{\frac{2v}{\mu}}x\right), \quad x \geq 0 \qquad (1)$$

where μ is half of the second moment, $v-1$ is the order of the modified Bessel function of the third kind, K_{v-1}, and $\Gamma(v)$ is the usual gamma function. Although K distribution has been considered the best fit for sea clutter, we observe that the fitting is not so good. In fact, we have found that the parameters from K distribution cannot effectively separate sea clutter data with and without target.

amplitude data by *y(n), n* = 1, 2, …, and the differenced data of sea clutter by *x(n) = y(n+1) – y(n), n* = 1, 2, … To fit the differenced data, we use the Tsallis distribution [16, 17],

$$p(x) = \frac{1}{Z_q}[1+\beta(q-1)x^2]^{1/(1-q)} \qquad (2)$$

where Zq is a normalization constant, β is related to the 2nd moment, and q is a parameter, whose deviation from 1 indicates non-extensivity of the physical process underlying the distribution: when $q = 1$, the distribution reduces to the Gaussian distribution; when $q = 2$, the distribution is the

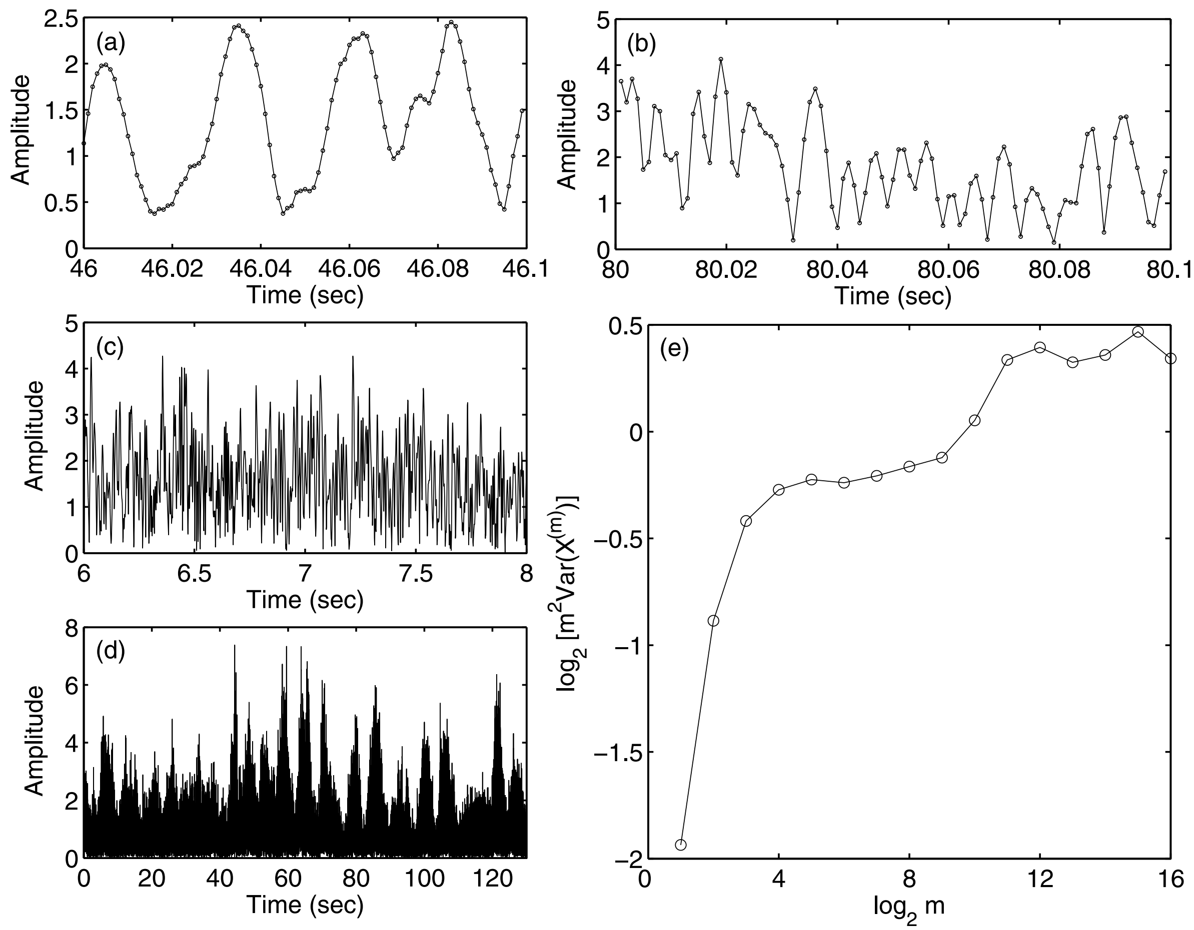


Figure 2 Example signal: (a,b) Two 0.1 sec duration sea clutter signals; (c) a 2 sec duration sea clutter signal; (d) the entire sea clutter signal (of about 130 sec); and (e) $\log_2[m^2 Var(X^{(m)})]$ vs. $\log_2 m$.

We hypothesize that the ineffectiveness of conventional distributional analysis is due to the non-stationarity in sea clutter caused by complicated interactions among ocean sprays, capillary waves, wind waves, and swells in the ocean. Differencing is often an effective means of eliminating non-stationarity. For example, the standard Brownian motion, when differenced, yields the independent Gaussian noise. Therefore, we propose to perform distributional analysis on the data obtained by differencing amplitude data of sea clutter. Denote the sea clutter

Cauchy distribution; when $5/3 < q < 3$, the distribution is heavy-tailed with infinite variance. It is important to note that Tsallis distribution is considered to provide a physical foundation to the α -stable distribution. The fitting using Tsallis distribution to the difference of the data used for Figure 3 (c,d) is shown in Figure 3(a,b). We observe that the shape of the density becomes simpler and the fitting is excellent. This signifies the importance of fitting the differenced data instead of the original sea clutter data and the usefulness of the Tsallis distribution.

Interestingly, the parameters from the Tsallis distribution are much more effective in detecting targets within sea clutter than the parameters from the K distribution. We shall not include any figures corroborating this here, however, since in the next section, we shall describe a multi-scale analysis method for detecting targets within sea clutter, which is even more accurate than that based on the parameters from the Tsallis distribution.

5. MULTI-SCALE METHOD FOR DETECTING TARGETS WITHIN SEA CLUTTER

One of the simplest multi-scale analyses is the structure-function based multifractal formulation [18, 19]. It is especially convenient for the study of the ubiquitous 1/f noise, a type of spatial or temporal variations whose power-spectral-density (PSD) decays in a power-law manner. Under this framework, the sea clutter data, $y(n)$, $n = 1, 2, \ldots$, is considered a "random walk" process, and one examines whether the following scaling-law holds or not,

$$F^{(q)}(N) = <|y(i+N) - y(i)|^q>^{1/q} \sim N^{H(q)}, \quad (3)$$

where $H(q)$ is a function of real value q, and the average is taken over all possible pairs of $(y(i+N), y(i))$. When the scaling laws described by Eq. (3) hold, the process under investigation is said to be a fractal process. Furthermore, if $H(q)$ is not a constant, the process is a multifractal; otherwise, it is a monofractal. The case of $q = 2$ is of special interest. It characterizes the correlation structure of the data set. In fact, when Eq. (3) holds, the autocorrelation for the "increment" process, defined as

$$x(i) = y(i+1) - y(i),$$

decays as a power-law,

$$r(k) \sim k^{2H(2)-2}, \text{ as } k - \propto,$$

while the PSD for $y(n)$, $n = 1, 2, \ldots$ is

$$E_y(f) \sim 1/f^{2H(2)+1}.$$

$H(2)$ is often called the Hurst parameter, and simply denoted as H. We have found that sea clutter data can be well described by Eq. (3) in the time scale range of 30 msec to about 1 sec, and that the $H(q)$ spectrum can accurately detect whether a range bin hit a target or not. Figure 4 shows a representative result for $q = 2$. We observe that $H(2)$ is much larger when the range bins hit a target. We have found that sea clutter data are multifractals, and that other q values can also robustly detect targets within sea clutter.

The accuracy of target detection within sea clutter critically depends on the time scale range of 30 msec to about 1 sec we identified. On time scales smaller than 30 msec, we have found that sea clutter data are actually quite smooth; on time scales longer than 1 sec, sea clutter data are very irregular, as shown in Figure 2. We hypothesize that different physical processes dominate on different time scales. Therefore, our method may be appropriately termed simultaneous characterization of multifractal properties of sea clutter and fractal scaling breaks on time scales determined by the physical processes underlying sea clutter.

6. CONCLUDING REMARKS

In this paper, we have shown that sea clutter data are highly non-stationary and multi-scaled. We have developed a new distributional analysis approach to describe sea clutter, and developed a multi-scale method for detecting low observable targets within sea clutter.

To fully understand the different physical processes underlying sea clutter, it would be very desirable to simultaneously characterize the behaviors of sea clutter on a wide range of scales. Our promising results presented here may be considered a first solid step toward this goal.

References

[1] F.A. Fay, J. Clarke, and R. S. Peters, "Weibull distribution applied to sea-clutter", *Proc. IEE Conf. Radar'77*, London, U.K., pp. 101-103, 1977.

[2] F.E. Nathanson, *Radar design principles* (McGraw Hill), pp. 254-256, 1969.

[3] E. Jakeman and P.N. Pusey, "A model for non Rayleigh sea echo", *IEEE Trans Antennas & Propagation*, 24, 806-814, 1976.

[4] S. Sayama and M. Sekine, "Log-normal, log-Weibull and K-distributed sea clutter", *IEICE Trans. Commun.* E85-B, 1375-1381, 2002.

[5] F. Gini, A. Farina, and M. Montanari, "Vector subspace detection in compound-Gaussian clutter, Part II: performance analysis", *IEEE Transactions on Aerospace and Electronic Systems* 38, 1312-1323, 2002.

[6] S. Haykin and S. Puthusserypady, "Chaotic dynamics of sea clutter". *Chaos*, 7, 777-802 (1997).

[7] S. Haykin, *Chaotic dynamics of sea clutter* (John Wiley) 1999.

[8] S. Haykin, R. Bakker, and B.W. Currie, Uncovering nonlinear dynamics-the case study of sea clutter, *Proc. IEEE* 90, 860-881 (2002).

[9] http://www.aspc.qinetiq.com/Events/July99/abstracts.html #Cowper

[10] M.R. Cowper and B. Mulgrew, "Nonlinear Processing of High Resolution Radar Sea Clutter," *Proc. IJCNN* 4, pp. 2633 (1999).

[11] M. Davies, "Looking for Non-Linearities in Sea Clutter," *IEE Radar and Sonar Signal Processing*, Peebles, Scotland, July 1998.

[12] J. L. Noga, "Bayesian State-Space Modelling of Spatio-Temporal Non-Gaussian Radar Returns", Ph.D thesis, Cambridge University, 1998.

[13] J.B. Gao and k. Yao, "Multifractal features of sea clutter", *IEEE Radar Conference 2002*, Long Beach, CA, April, 2002.

[14] J.B. Gao, S.K. Hwang, H.F. Chen, Z. Kang, K. Yao, and J.M. Liu, "Can sea clutter and indoor radio propagation be modeled as strange attractors?" *The 7th Experimental Chaos Conference*, San Diego, USA, August 25-29, 2002.

[15] M. McDonald and A. Damini, "Limitations of nonlinear chaotic dynamics in predicting sea clutter returns", *IEE Proc-Radar Son Nav* 151, 105-113 (2004).

[16] C. Tsallis, S.V.F. Levy, A.M.C. Souza, and R. Maynard, Statistical-Mechanical Foundation of the Ubiquity of Levy Distributions in Nature, *Phys. Rev. Lett.* 75, 3589-3593, 1995.

[17] C. Beck, G.S. Lewis, and H.L. Swinney, Measuring nonextensitivity parameters in a turbulent Couette-Taylor flow, *Phys. Rev. E* 63, 035303(R), 2001.

[18] J.B. Gao, J. Hu, W.W. Tung, Y.H. Cao, N. Sarshar, V.P. Roychowdhury, Assessment of long range correlation in time series: How to avoid pitfalls. *Phys. Rev. E* 73, 016117 (2006).

[19] J.B. Gao, Y.H. Cao, W.W. Tung, and J. Hu, *Multiscale Analysis of Complex Time Series — Integration of Chaos and Random Fractal Theory, and Beyond*, Wiley Interscience, New York, Sept., 2007, pp. 352.

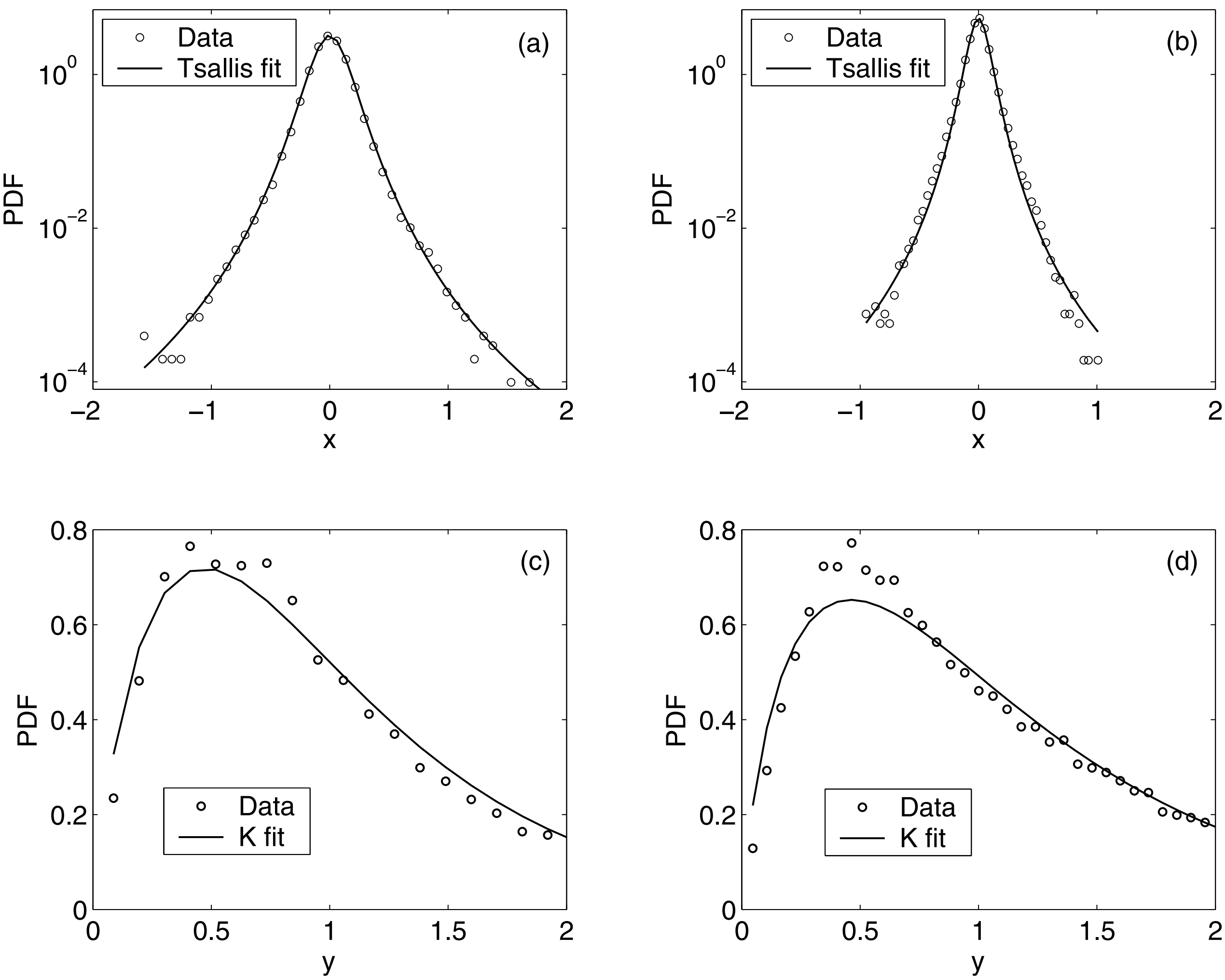


Figure 3 Representative results of using (a,b) Tsallis distribution to fit the differenced data and (c,d) K distribution to fit the amplitude data of sea clutter. (a,c) are for the sea clutter data without target, while (b,d) are for the data with target. Circles and solid lines denote the raw and fitted probability density functions (PDFs), respectively.

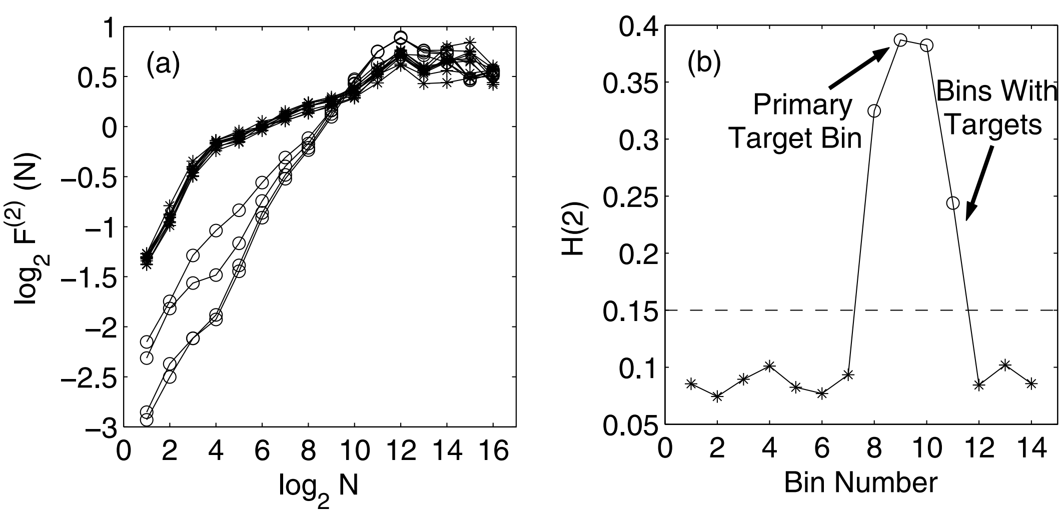
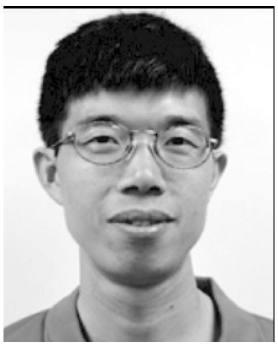


Figure 4 (a) $\log_2 F^{(2)}(N)$ vs. $\log_2 N$ for the 14 range bins; (b) The *H*(2) values for the 14 range bins. Open circles denote bins with target, while * denote bins without targets.

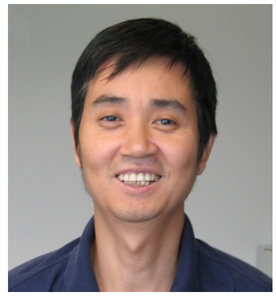
BIOGRAPHY

Jing Hu *received the B.Sc. and M.Eng. degrees in electrical engineering from Huazhong University of Science and Technology, Wuhan, China, in 2000 and 2002, respectively. She got the Ph.D. from the Electrical and Computer Engineering department at the University of Florida in May 2007, under the supervision of Prof. Jianbo Gao. Her major research focus is multi-scale analysis of nonlinear signals, with emphasis on biomedical signal processing and modeling, as well as radar engineering.*



Jianbo Gao *is an Assistant Professor at the University of Florida. He has been working on a number of different fields including nano- and fault-tolerant computing, nonlinear time series analysis, traffic modeling in communications networks, nonlinear dynamics of the Internet, characterization of non-Gaussian noise in radio communications channels, biological data analysis and bioinformatics. Some of the tools he developed have been applied to study a wide range of real world signal processing problems arising from as diverse fields as physics, geophysics, biology, economics, and engineering. He received the outstanding young scientist award from Chinese Academy of Sciences in Sept. 1993. He is an associate editor for IEEE Trans. Biomedical Engineering.*

Robert S. Lynch *is a senior electronics engineer with the Naval Undersea Warfare Center in Newport, RI, where he is involved in the research and development of sonar systems. In 1984 and 1991, respectively, he received BS and MS degrees, both in Electrical Engineering, from Union College in Schenectady, NY. In 1999 he received a PhD in Electrical Engineering from the University of Connecticut, Storrs, CT. His research interests are in the areas of pattern recognition and classification, detection, data fusion, tracking, and signal processing. In addition to the IEEE he is also a member of the International Society of Information Fusion (ISIF), and is an associate member of the Sensor, Array, and Multichannel (SAM) Technical Committee. Dr. Lynch is an Associate Editor of the IEEE Transactions on Systems, Man, and Cybernetics Part B, Cybernetics.*



Genshe Chen *received his B. S. and M. S. in electrical engineering, Ph. D in aerospace engineering, in 1989, 1991 and 1994 respectively, all from Northwestern Polytechnical University, Xian, P. R. China. He did postdoctoral work at the Beijing University of Aeronautics and Astronautics and Wright State University from 1994 to 1997. He worked at the Institute of Flight Guidance and Control of the Technical University of Braunshweig (Germany) as an Alexander von Humboldt research fellow and at the Flight Division of National Aerospace Laboratory of Japan as a STA fellow from 1997 to 2001. He was a Postdoctoral Research Associate in the Department of Electrical and Computer Engineering of The Ohio State University from 2002 to 2004. Since February 2004, Dr. Chen has been with the Intelligent Automation, Inc., Rockville, MD. He has served as the Principal Investigator/Technical lead for more than 15 different projects, including maneuvering target detection and tracking, joint ATR and tracking, cooperative control for teamed unmanned aerial vehicles, a stochastic differential pursuit-evasion game with multiple players, multi-missile interception, asymmetric threat detection and prediction, space situation awareness, and cyber defense, etc. He is currently the program manager in Networks, Systems and Control, leading research and development efforts in target tracking, information fusion and cooperative control. His research interests include guidance and control of aerospace vehicle, GPS/INS/image integrated navigation systems, target tracking and information fusion, cooperative control and optimization for military operations, computational intelligence and data mining, hybrid system theory and Markov chain, signal processing and computer vision, cooperative and non-cooperative game theory, Bayesian networks, Influence Diagram, and GIS.*