

## Research Article

# On the Predictability of Long-Range Dependent Series

Ming Li<sup>1</sup> and Jia-Yue Li<sup>2</sup>

<sup>1</sup> School of Information Science & Technology, East China Normal University, Dong-Chuan Road no. 500, Shanghai 200241, China

<sup>2</sup> Key Laboratory of Geographical Information Science, Ministry of Education of China; School of Resources and Environment Science, East China Normal University, Shanghai 200062, China

Correspondence should be addressed to Ming Li, ming\_lihk@yahoo.com

Received 23 January 2010; Accepted 7 February 2010

Academic Editor: Cristian Toma

Copyright © 2010 M. Li and J.-Y. Li. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

This paper points out that the predictability analysis of conventional time series may in general be invalid for long-range dependent (LRD) series since the conventional mean-square error (MSE) may generally not exist for predicting LRD series. To make the MSE of LRD series prediction exist, we introduce a generalized MSE. With that, the proof of the predictability of LRD series is presented in Hilbert space.

## 1. Introduction

Let  $x(t)$  be a realization, which is a second-order random function for  $t \in [0, \infty)$ . Let  $x_T(t)$  be a given sample of  $x(t)$  for  $0 \leq t \leq T$ . Then, one of the important problems in time series is to predict or forecast  $x(t)$  for  $t > T$  based on the known realizations of  $x_T(t)$ ; see, for example, Clements and Hendry [1], Box et al. [2], and Fuller [3].

A well-known case in the field of time series prediction refers to Yule's work for the analysis of Wolfer's sunspot numbers (Yule [4]). The early basic theory of predicting a 2nd-order stationary random function in the conventional sense refers to the work of Wiener [5] and Kolmogorov [6]. By conventional sense, we mean that the stationary random functions Wiener and Kolmogorov considered are not long-range dependent (LRD). In other words, the time series they studied have finite mean and variance. Consequently, they in general are not heavy tailed as can be seen from Zadeh and Ragazzini [7], Bhansali [8], and Robinson [9].

The predictability of conventional time series has been well studied; see, for example, Papoulis [10], Vaidyanathan [11], Bhansali [12], Lyman et al. [13], Lyman and Edmonson

[14], and Dokuchaev [15]. The basic idea in this regard is to use mean-square error (MSE) as a constraint to obtain a prediction; see, for example, Harrison et al. [16], Bellegem and Sachs [17], Man [18], as well as Clements and Hendry [19]. We shall note in next section that the conventional MSE may in general fail to be used for predicting LRD series.

LRD processes gain increasing applications in various fields of sciences and technologies; see, for example, Beran [20], Mandelbrot [21], Cattani et al. [22], and Li et al. [23–29]. Consequently, the prediction is desired for LRD series. The literature regarding the prediction of LRD series appears to be increasing; see, for example, Brodsky and Hurvich [30], Reisen and Lopes [31], Bisaglia and Bordignon [32], Bhansali and Kokoszka [33], Man [34], Bayraktar et al. [35], Man and Tiao [36], Bisaglia and Gerolimetto [37], Godet [38], as well as Gooijer and Hyndman [39]. However, unfortunately, suitable MSE used for predicting LRD series may be overlooked, leaving a pitfall in this respect. We shall present a generalized MSE in the domain of generalized functions for the purpose of proving the existence of LRD series prediction.

The rest of this article is arranged as follows. Section 2 will point out the pitfall of prediction of time series based on traditional MSE. The proof of the predictability of LRD series will be proposed in Section 3, which is followed by discussions and conclusions.

## 2. Problem Statement

Denote the autocorrelation function (ACF) of  $x(t)$  by  $r_{xx}(\tau)$ , where  $r_{xx}(\tau) = E[x(t)x(t + \tau)]$ . Then,  $x(t)$  is called short-range dependent (SRD) series if  $r_{xx}(\tau)$  is integrable (Beran [20]), that is,

$$\int_0^{\infty} r_{xx}(\tau) d\tau < \infty. \quad (2.1)$$

On the other side,  $x(t)$  is long-range dependent (LRD) if  $r_{xx}(\tau)$  is nonintegrable, that is,

$$\int_0^{\infty} r_{xx}(\tau) d\tau = \infty. \quad (2.2)$$

A typical form of such an ACF has the following asymptotic expression:

$$r_{xx}(\tau) \sim c|\tau|^{-\beta} (\tau \rightarrow \infty), \quad (2.3)$$

where  $c > 0$  is a constant and  $0 < \beta < 1$ .

Denote the probability density function (PDF) of  $x(t)$  by  $p(x)$ . Then, the ACF of  $x(t)$  can be expressed by

$$r_{xx}(\tau) = \int_{-\infty}^{\infty} x(t)x(t + \tau)p(x) dx. \quad (2.4)$$

Considering that  $r_{xx}(\tau)$  is nonintegrable, we see that a heavy-tailed PDF is a consequence of LRD series; see, for example, Resnick [40], Heath et al. [41], Paxson and Floyd [42], Li [23, 24, 43], Abry et al. [44], as well as Adler et al. [45].

Denote  $\mu_x$  by the mean of  $x(t)$ . Then,

$$\mu_x = \int_{-\infty}^{\infty} xp(x)dx. \quad (2.5)$$

The variance of  $x(t)$  is given by

$$\text{Var}(x) = \int_{-\infty}^{\infty} (x - \mu_x)^2 p(x)dx. \quad (2.6)$$

One remarkable thing in LRD series is that the tail of  $p(x)$  may be so heavy that the above integral either (2.5) or (2.6) does not exist (Bassingthwaighte et al. [46], Doukhan et al. [47], Li [48]). To explain this, we utilize the Pareto distribution. Denote  $p_{\text{Pareto}}(x)$  the PDF of the Pareto distribution. Then (G. A. Korn and T. M. Korn [49]),

$$p_{\text{Pareto}}(x) = \frac{ab}{x^{a+1}}, \quad (2.7)$$

where  $x \geq a$ . The mean and variance of  $x(t)$  that follows  $p_{\text{Pareto}}(x)$  are, respectively, given by

$$\mu_{\text{Pareto}} = \frac{ab}{a-1}, \quad (2.8)$$

$$\text{Var}(x)_{\text{Pareto}} = \frac{ab^2}{(a-1)^2(a-2)}. \quad (2.9)$$

It can be easily seen that  $\mu_{\text{Pareto}}$  and  $\text{Var}(x)_{\text{Pareto}}$  do not exist if  $a = 1$ .

Following the work of Kolmogorov's, a linear prediction can be expressed as follows. Given  $n > 0$  and  $m \geq 0$ , the selection of proper real coefficient  $a_s$  is such that the following linear combination of random variables  $x(t-1), x(t-2), \dots, x(t-n)$  given by

$$L = \sum_{i=1}^n a_i x(t-i) \quad (2.10)$$

can approximate  $x(t+m)$  as accurately as possible (Kolmogorov [6]). The following MSE is usually chosen as the prediction criterion of (2.10):

$$\sigma^2 \triangleq \sigma^2(n, m) = E[x(t+m) - L]^2. \quad (2.11)$$

By minimizing (2.11), one has the desired  $a_i$  in (2.10). Wiener well studied that criterion for both prediction and filtering; see, for example, Levinson [50, 51]. A predictor following (2.10) and (2.11) can be regarded in the class of Wiener-Kolmogorov predictors.

Various forms of linear combination in terms of (2.10) have been developed, such as autoregressive moving average (ARMA) model, autoregressive (AR) model, moving average (MA) model, and autoregressive integrated moving average (ARIMA); see, for example, Lyman et al. [13], Lyman and Edmonson [14], Wolff et al. [52], Bhansali [12, 53], Markhouli [54], Kohn and Ansley [55], Zimmerman and Cressie [56], Peiris and Perera [57], Kudritskii [58], Bisaglia and Bordignon [59], Kim [60], Cai [61], Harvill and Ray [62], Atal [63], Huang [64], Schick and Wefelmeyer [65], Jamalizadeh and Balakrishnan [66], Clements and Hendry [1], and Box et al. [2]. However, one thing in common for different forms of predictors is to minimize prediction error that in principle usually follows the form of (2.11).

Note that the necessary condition for the above-described Wiener-Kolmogorov predictor to be valid is that  $E[x(t)]$  exists (Kolmogorov [6]). For LRD series, however, it may not always be satisfied. For instance, if an LRD series obeys the Pareto distribution, its mean does not exist for  $a = 1$ ; see (2.8).

In addition to the fact that the mean of an LRD series may not exist, its variance may not exist either. The error in (2.11) can be expressed by

$$\sigma^2(n, m) = E[x(t+m) - L]^2 = \int_{-\infty}^{\infty} [x(t+m) - L]^2 p(x) dx. \quad (2.12)$$

Kolmogorov stated that the above  $\sigma^2(n, m)$  does not increase as  $n$  increases [6]. However, that statement may be untrue if  $x(t)$  is LRD.

It is worth noting that errors may be heavy tailed; see, for example, Peng and Yao [67] as well as Hall and Yao [68]. For instance, LRD teletraffic is heavy tailed with the possible heavy-tail model of Pareto (Resnick [69], Michiel and Laevens [70]) and it is Gaussian at large time scales (Paxson and Floyd [71], Scherrer et al. [72]). Therefore, it is quite reasonable to assume that  $[x(t+m) - L]$  follows a heavy-tailed distribution, for example, the Pareto distribution, for the purpose of this presentation. If it obeys the Pareto one, then the above expression approaches infinite for  $a = 2$  (see (2.9)) no matter how large  $n$  is.

From the above discussions, we see that it may be unsuitable to use the conventional MSE as used in the class of conventional Wiener-Kolmogorov predictors to infer that LRD series is predictable. In the next section, we shall give the proof of the predictability of LRD series.

### 3. Predictability of LRD Series

Let  $x(t+m) \in X$ , where  $X$  is the set of LRD processes. Let  $L \in \hat{X}$ . Then,  $\hat{X} \subseteq X$ . We now consider the norms and inner products in  $\hat{X}$  and  $X$ .

*Definition 3.1* (see [73]). A function of rapid decay is a smooth function  $\phi : \mathbb{R} \rightarrow \mathbb{C}$  such that  $t^n \phi^{(r)}(t) \rightarrow 0$  as  $t \rightarrow \pm\infty$  for all  $n, r \geq 0$ , where  $\mathbb{C}$  is the space of complex numbers. The set of all functions of rapid decay is denoted by  $\mathcal{S}$ .

In the discrete case, the rapid decayed function is denoted by  $\phi(n)$  and we still use the symbol  $\mathcal{S}$  to specify the space it belongs to for the simplicity without confusions.

**Lemma 3.2** (see [73]). *Every function belonging to  $\mathcal{S}$  is absolutely integrable in the continuous case or absolutely summable in the discrete case.*

Now, define the norm of  $x(t + m) \in X$  by

$$\|x(t + m)\|^2 = \langle x(t + m), x(t + m) \rangle = \int_{-\infty}^{\infty} x^2(t + m)p(x)g(x)dx, \quad (3.1)$$

where  $g \in \mathcal{S}$ . Define the inner product of  $x(t + m) \in X$  by

$$\langle x(t + m), x(t + m) \rangle = \|x(t + m)\|^2. \quad (3.2)$$

Then, combining any  $x(t + m) \in X$  with its limit makes  $X$  a Hilbert space.

Note that

$$\|L\|^2 = \langle L, L \rangle = \int_{-\infty}^{\infty} L^2 p(x)g(x)dx. \quad (3.3)$$

Then,  $\hat{X}$  is the closed subset of  $X$ .

**Lemma 3.3** (see [73–75], Existence of a unique minimizing element in Hilbert space). *Let  $\mathcal{H}$  be a Hilbert space and let  $\mathcal{M}$  be a closed convex subset of  $\mathcal{H}$ . Let  $x \in \mathcal{H}$ ,  $x \notin \mathcal{M}$ . Then, there exists a unique element  $\hat{x} \in \mathcal{M}$  satisfying*

$$\|x - \hat{x}\| = \inf_{y \in \mathcal{M}} \|x - y\|. \quad (3.4)$$

**Theorem 3.4.** *Let  $L$  be a linear combination of the past values of  $x(n)$  according to (2.10). Then, there exists a unique  $L \in \hat{X}$  such that  $\|L - x(t + m)\| = \inf_{s \in \hat{X}} \|x(t + m) - s\|$ .*

*Proof.*  $X$  is a Hilbert space.  $\hat{X}$  is its closed subset and it is obviously convex. According to Lemma 3.3, for any  $x(t + m) \in X$ , there exists a unique  $L \in \hat{X} \subseteq X$  such that  $\|L - x(t + m)\| = \inf_{s \in \hat{X}} \|x(t + m) - s\|$ .  $\square$

The above theorem exhibits that LRD series are predictable in the sense that the mean-square error expressed by (2.12) is in general generalized to the following for  $g \in \mathcal{S}$ :

$$\sigma^2(n, m) = E[x(t + m) - L]^2 = \int_{-\infty}^{\infty} [x(t + m) - L]^2 p(x)g(x)dx. \quad (3.5)$$

## 4. Discussions and Conclusions

LRD series considerably differ from the conventional series; see, for example, Beran [20, 76], Adler et al. [45], Doukhan et al. [47], as well as Künsch et al. [77]. Examples mentioned in this regard are regressions for fitting LRD models (Peng and Yao [67], Beran [78], and Beran et al. [79]), variance analysis of autocorrelation estimation (Li and Zhao [80]), stationarity test (Li et al. [81]), power spectra (Li and Lim [82, 83]), and [84–91]. This paper addresses the particularity of the predictability of LRD series. We have given a proof of LRD series being predictable. As a side product obtained from the proof procedure, the mean-square error used by Kolmogorov as a criterion of LRD series prediction has been generalized to be the form of (3.5).

## Acknowledgments

This work was partly supported by the National Natural Science Foundation of China (NSFC) under the project Grant numbers 60573125, 60873264, 60703112, and 60873168 and the National High Technology Research and Development Program (863) of China under Grant no. 2009AA01Z418.

## References

- [1] M. P. Clements and D. F. Hendry, *Forecasting Economic Time Series*, Cambridge University Press, Cambridge, UK, 1998.
- [2] G. E. P. Box, G. M. Jenkins, and G. C. Reinsel, *Time Series Analysis: Forecasting and Control*, Prentice-Hall, Englewood Cliffs, NJ, USA, 3rd edition, 1994.
- [3] W. A. Fuller, *Introduction to Statistical Time Series*, Wiley Series in Probability and Statistics: Probability and Statistics, John Wiley & Sons, New York, NY, USA, 2nd edition, 1995.
- [4] G. Udny Yule, "On a method of investigating periodicities in disturbed series, with special reference to Wolfer's sunspot numbers," *Philosophical Transactions of the Royal Society A*, vol. 226, no. 636–646, pp. 267–297, 1927.
- [5] N. Wiener, *Extrapolation, Interpolation and Smoothing of Stationary Time Series*, John Wiley & Sons, New York, NY, USA; The MIT Press, Cambridge, Mass, USA, 1964.
- [6] A. N. Kolmogorov, "Interpolation and extrapolation of stationary random sequences," *Izvestiya Akademii Nauk SSSR*, vol. 5, pp. 3–14, 1941.
- [7] L. A. Zadeh and J. R. Ragazzini, "An extension of Wiener's theory of prediction," *Journal of Applied Physics*, vol. 21, pp. 645–655, 1950.
- [8] R. J. Bhansali, "Asymptotic properties of the Wiener-Kolmogorov predictor. I," *Journal of the Royal Statistical Society*, vol. 36, no. 1, pp. 61–73, 1974.
- [9] E. A. Robinson, "A historical perspective of spectrum estimation," *Proceedings of the IEEE*, vol. 70, no. 9, pp. 885–907, 1982.
- [10] A. Papoulis, "A note on the predictability of band-limited processes," *Proceedings of the IEEE*, vol. 73, no. 8, pp. 1332–1333, 1985.
- [11] P. P. Vaidyanathan, "On predicting a band-limited signal based on past sample values," *Proceedings of the IEEE*, vol. 75, no. 8, pp. 1125–1159, 1987.
- [12] R. J. Bhansali, "Linear prediction by autoregressive model fitting in the time domain," *The Annals of Statistics*, vol. 6, no. 1, pp. 224–231, 1978.
- [13] R. J. Lyman, W. W. Edmonson, S. McCullough, and M. Rao, "The predictability of continuous-time, bandlimited processes," *IEEE Transactions on Signal Processing*, vol. 48, no. 2, pp. 311–316, 2000.
- [14] R. J. Lyman and W. W. Edmonson, "Linear prediction of bandlimited processes with flat spectral densities," *IEEE Transactions on Signal Processing*, vol. 49, no. 7, pp. 1564–1569, 2001.
- [15] N. Dokuchaev, "The predictability of band-limited, high-frequency and mixed processes in the presence of ideal low-pass filters," *Journal of Physics A*, vol. 41, no. 38, Article ID 382002, 7 pages, 2008.
- [16] R. Harrison, G. Kapetanios, and T. Yates, "Forecasting with measurement errors in dynamic models," *International Journal of Forecasting*, vol. 21, no. 3, pp. 595–607, 2005.
- [17] S. van Bellegem and R. von Sachs, "Forecasting economic time series with unconditional time-varying variance," *International Journal of Forecasting*, vol. 20, no. 4, pp. 611–627, 2004.
- [18] K. S. Man, "Linear prediction of temporal aggregates under model misspecification," *International Journal of Forecasting*, vol. 20, no. 4, pp. 659–670, 2004.
- [19] M. P. Clements and D. F. Hendry, "Forecasting economic processes," *International Journal of Forecasting*, vol. 14, no. 1, pp. 111–131, 1998.
- [20] J. Beran, *Statistics for Long-Memory Processes*, vol. 61 of *Monographs on Statistics and Applied Probability*, Chapman and Hall, New York, NY, USA, 1994.
- [21] B. B. Mandelbrot, *Gaussian Self-Affinity and Fractals*, Springer, New York, NY, USA, 2001.
- [22] C. Cattani, M. Li, and C. Toma, "Short range phenomena: modeling, computational aspects and applications," *Mathematical Problems in Engineering*, vol. 2008, Article ID 761081, 2 pages, 2008.
- [23] M. Li, "Fractal time series—a tutorial review," *Mathematical Problems in Engineering*, vol. 2010, Article ID 157264, 26 pages, 2010.

- [24] M. Li, "Generation of teletraffic of generalized Cauchy type," *Physica Scripta*, vol. 81, no. 2, p. 10, 2010.
- [25] M. Li and W. Zhao, "Representation of a stochastic traffic bound," to appear in *IEEE Transactions on Parallel and Distributed Systems*.
- [26] M. Li and P. Bognat, "Forward for the special issue on traffic modeling, its computations and applications," to appear in *Telecommunication Systems*.
- [27] M. Li and S. C. Lim, "Modeling network traffic using generalized Cauchy process," *Physica A*, vol. 387, no. 11, pp. 2584–2594, 2008.
- [28] M. Li, "An approach to reliably identifying signs of DDOS flood attacks based on LRD traffic pattern recognition," *Computers and Security*, vol. 23, no. 7, pp. 549–558, 2004.
- [29] M. Li, "Change trend of averaged Hurst parameter of traffic under DDOS flood attacks," *Computers and Security*, vol. 25, no. 3, pp. 213–220, 2006.
- [30] J. Brodsky and C. M. Hurvich, "Multi-step forecasting for long-memory processes," *Journal of Forecasting*, vol. 18, no. 1, pp. 59–75, 1999.
- [31] V. A. Reisen and S. Lopes, "Some simulations and applications of forecasting long-memory time-series models," *Journal of Statistical Planning and Inference*, vol. 80, no. 1-2, pp. 269–287, 1999.
- [32] L. Bisaglia and S. Bordignon, "Mean square prediction error for long-memory processes," *Statistical Papers*, vol. 43, no. 2, pp. 161–175, 2002.
- [33] R. J. Bhansali and P. S. Kokoszka, "Prediction of long-memory time series: a tutorial review," in *Processes with Long-Range Correlations*, vol. 621 of *Lecture Notes in Physics*, pp. 3–21, Springer, Berlin, Germany, 2003.
- [34] K. S. Man, "Long memory time series and short term forecasts," *International Journal of Forecasting*, vol. 19, no. 3, pp. 477–491, 2003.
- [35] E. Bayraktar, H. V. Poor, and R. Rao, "Prediction and tracking of long-range-dependent sequences," *Systems & Control Letters*, vol. 54, no. 11, pp. 1083–1090, 2005.
- [36] K. S. Man and G. C. Tiao, "Aggregation effect and forecasting temporal aggregates of long memory processes," *International Journal of Forecasting*, vol. 22, no. 2, pp. 267–281, 2006.
- [37] L. Bisaglia and M. Gerolimetto, "Forecasting long memory time series when occasional breaks occur," *Economics Letters*, vol. 98, no. 3, pp. 253–258, 2008.
- [38] F. Godet, "Prediction of long memory processes on same-realisation," *Journal of Statistical Planning and Inference*, vol. 140, no. 4, pp. 907–926, 2010.
- [39] J. G. De Gooijer and R. J. Hyndman, "25 years of time series forecasting," *International Journal of Forecasting*, vol. 22, no. 3, pp. 443–473, 2006.
- [40] S. I. Resnick, *Heavy-Tail Phenomena: Probabilistic and Statistical Modeling*, Springer Series in Operations Research and Financial Engineering, Springer, New York, NY, USA, 2007.
- [41] D. Heath, S. Resnick, and G. Samorodnitsky, "Heavy tails and long range dependence in ON/OFF processes and associated fluid models," *Mathematics of Operations Research*, vol. 23, no. 1, pp. 145–165, 1998.
- [42] V. Paxson and S. Floyd, "Wide area traffic: the failure of Poisson modeling," *IEEE/ACM Transactions on Networking*, vol. 3, no. 3, pp. 226–244, 1995.
- [43] M. Li, "Fractional Gaussian noise and network traffic modeling," in *Proceedings of the 8th WSEAS International Conference on Applied Computer and Applied Computational Science*, pp. 34–39, Hangzhou, China, May 2009.
- [44] P. Abry, P. Borgnat, F. Ricciato, A. Scherrer, and D. Veitch, "Revisiting an old friend: on the observability of the relation between long range dependence and heavy tail," to appear in *Telecommunication Systems*.
- [45] R. J. Adler, R. E. Feldman, and M. S. Taqqu, Eds., *A Practical Guide to Heavy Tails: Statistical Techniques and Applications*, Birkhäuser, Boston, Mass, USA, 1998.
- [46] J. B. Bassingthwaighte, L. S. Liebovitch, and B. J. West, *Fractal Physiology*, Oxford University Press, Oxford, UK, 1994.
- [47] P. Doukhan, G. Oppenheim, and M. S. Taqqu, Eds., *Theory and Applications of Long-Range Dependence*, Birkhäuser, Boston, Mass, USA, 2003.
- [48] M. Li, *Teletraffic Modeling Relating to Generalized Cauchy Process: Empirical Study*, VDM, Saarbrücken, Germany, 2009.
- [49] G. A. Korn and T. M. Korn, *Mathematical Handbook for Scientists and Engineers*, McGraw-Hill, Boston, Mass, USA, 1961.
- [50] N. Levinson, "The Wiener RMS (root mean square) error criterion in filter design and prediction," *Journal of Mathematics and Physics*, vol. 25, pp. 261–278, 1947.

- [51] N. Levinson, "A heuristic exposition of Wiener's mathematical theory of prediction and filtering," *Journal of Mathematics and Physics*, vol. 26, pp. 110–119, 1947.
- [52] S. S. Wolff, J. L. Gastwirth, and J. B. Thomas, "Linear optimum predictors," *IEEE Transactions on Information Theory*, vol. 13, no. 1, pp. 30–32, 1967.
- [53] R. J. Bhansali, "Asymptotic mean-square error of predicting more than one-step ahead using the regression method," *Journal of the Royal Statistical Society. Series C*, vol. 23, pp. 35–42, 1974.
- [54] J. Markhoul, "Linear prediction: a tutorial review," *Proceedings of the IEEE*, vol. 63, no. 4, pp. 561–580, 1975.
- [55] R. Kohn and C. F. Ansley, "Estimation, prediction, and interpolation for ARIMA models with missing data," *Journal of the American Statistical Association*, vol. 81, no. 395, pp. 751–761, 1986.
- [56] D. L. Zimmerman and N. Cressie, "Mean squared prediction error in the spatial linear model with estimated covariance parameters," *Annals of the Institute of Statistical Mathematics*, vol. 44, no. 1, pp. 27–43, 1992.
- [57] M. S. Peiris and B. J. C. Perera, "On prediction with fractionally differenced ARIMA models," *Journal of Time Series Analysis*, vol. 9, no. 3, pp. 215–220, 1988.
- [58] V. D. Kudritskii, "Optimal linear extrapolation algorithm for realization of a vector random sequence observed without errors," *Cybernetics and Systems Analysis*, vol. 34, no. 2, pp. 185–189, 1998.
- [59] L. Bisaglia and S. Bordignon, "Mean square prediction error for long-memory processes," *Statistical Papers*, vol. 43, no. 2, pp. 161–175, 2002.
- [60] J. H. Kim, "Forecasting autoregressive time series with bias-corrected parameter estimators," *International Journal of Forecasting*, vol. 19, no. 3, pp. 493–502, 2003.
- [61] Y. Cai, "A forecasting procedure for nonlinear autoregressive time series models," *Journal of Forecasting*, vol. 24, no. 5, pp. 335–351, 2005.
- [62] J. L. Harvill and B. K. Ray, "A note on multi-step forecasting with functional coefficient autoregressive models," *International Journal of Forecasting*, vol. 21, no. 4, pp. 717–727, 2005.
- [63] B. S. Atal, "The history of linear prediction," *IEEE Signal Processing Magazine*, vol. 23, no. 2, pp. 154–161, 2006.
- [64] D. W. Huang, "Levinson-type recursive algorithms for least-squares autoregression," *Journal of Time Series Analysis*, vol. 11, no. 4, pp. 295–315, 1990.
- [65] A. Schick and W. Wefelmeyer, "Prediction in moving average processes," *Journal of Statistical Planning and Inference*, vol. 138, no. 3, pp. 694–707, 2008.
- [66] A. Jamalizadeh and N. Balakrishnan, "Prediction in a trivariate normal distribution via a linear combination of order statistics," *Statistics & Probability Letters*, vol. 79, no. 21, pp. 2289–2296, 2009.
- [67] L. Peng and Q. Yao, "Nonparametric regression under dependent errors with infinite variance," *Annals of the Institute of Statistical Mathematics*, vol. 56, no. 1, pp. 73–86, 2004.
- [68] P. Hall and Q. Yao, "Inference in ARCH and GARCH models with heavy-tailed errors," *Econometrica*, vol. 71, no. 1, pp. 285–317, 2003.
- [69] S. I. Resnick, "Heavy tail modeling and teletraffic data: special invited paper," *The Annals of Statistics*, vol. 25, no. 5, pp. 1805–1869, 1997.
- [70] H. Michiel and K. Laevens, "Teletraffic engineering in a broad-band era," *Proceedings of the IEEE*, vol. 85, no. 12, pp. 2007–2032, 1997.
- [71] V. Paxson and S. Floyd, "Wide area traffic: the failure of Poisson modeling," *IEEE/ACM Transactions on Networking*, vol. 3, no. 3, pp. 226–244, 1995.
- [72] A. Scherrer, N. Larrieu, P. Owezarski, P. Borgnat, and P. Abry, "Non-Gaussian and long memory statistical characterizations for internet traffic with anomalies," *IEEE Transactions on Dependable and Secure Computing*, vol. 4, no. 1, pp. 56–70, 2007.
- [73] D. H. Griffel, *Applied Functional Analysis*, Ellis Horwood Series in Mathematics and Its Application, Ellis Horwood, Chichester, UK, 1981.
- [74] C. K. Liu, *Applied Functional Analysis*, Defence Industry Press, Beijing, China, 1986.
- [75] M. Li, "Modeling autocorrelation functions of long-range dependent teletraffic series based on optimal approximation in Hilbert space—a further study," *Applied Mathematical Modelling*, vol. 31, no. 3, pp. 625–631, 2007.
- [76] J. Beran, "Statistical methods for data with long-range dependence," *Statistical Science*, vol. 7, no. 4, pp. 404–416, 1992.
- [77] H. Künsch, J. Beran, and F. Hampel, "Contrasts under long-range correlations," *The Annals of Statistics*, vol. 21, no. 2, pp. 943–964, 1993.



- [78] J. Beran, "Fitting long-memory models by generalized linear regression," *Biometrika*, vol. 80, no. 4, pp. 817–822, 1993.
- [79] J. Beran, S. Ghosh, and D. Schell, "On least squares estimation for long-memory lattice processes," *Journal of Multivariate Analysis*, vol. 100, no. 10, pp. 2178–2194, 2009.
- [80] M. Li and W. Zhao, "Variance bound of ACF estimation of one block of fGn with LRD," *Mathematical Problems in Engineering*, vol. 2010, Article ID 560429, 14 pages, 2010.
- [81] M. Li, W.-S. Chen, and L. Han, "Correlation matching method of the weak stationarity test of LRD traffic," to appear in *Telecommunication Systems*.
- [82] M. Li and S. C. Lim, "Power spectrum of generalized Cauchy process," to appear in *Telecommunication Systems*.
- [83] M. Li and S. C. Lim, "A rigorous derivation of power spectrum of fractional Gaussian noise," *Fluctuation and Noise Letters*, vol. 6, no. 4, pp. C33–C36, 2006.
- [84] G. Toma, "Specific differential equations for generating pulse sequences," *Mathematical Problems in Engineering*, vol. 2010, Article ID 324818, 11 pages, 2010.
- [85] Z.-H. Liu, "Chaotic time series analysis," to appear in *Mathematical Problems in Engineering*.
- [86] E. G. Bakhoun and C. Toma, "Mathematical transform of traveling-wave equations and phase aspects of quantum interaction," *Mathematical Problems in Engineering*, vol. 2010, Article ID 695208, 15 pages, 2010.
- [87] G. Toma and F. Doboga, "Vanishing waves on closed intervals and propagating short-range phenomena," *Mathematical Problems in Engineering*, vol. 2008, Article ID 359481, 14 pages, 2008.
- [88] E. G. Bakhoun and C. Toma, "Relativistic short range phenomena and space-time aspects of pulse measurements," *Mathematical Problems in Engineering*, vol. 2008, Article ID 410156, 20 pages, 2008.
- [89] C. Cattani, "Harmonic wavelet approximation of random, fractal and high frequency signals," to appear in *Telecommunication Systems*.
- [90] C. Cattani, "Harmonic wavelet analysis of a localized fractal," *International Journal of Engineering and Interdisciplinary Mathematics*, vol. 1, no. 1, pp. 35–44, 2009.
- [91] C. Cattani, "Shannon wavelets theory," *Mathematical Problems in Engineering*, vol. 2008, Article ID 164808, 24 pages, 2008.