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Adaptive spectral estimation for nonstationary multivariate time series

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ABSTRACT

Following the nonstationary univariate time series model of Rosen et al. (2012), we propose an adaptive estimation of time-varying spectra and cross-spectra for analyzing possibly nonstationary multivariate time series. Under the Bayesian framework, the estimation is implemented by smoothing stochastic approximation Monte Carlo (SSAMC) methods. We show by simulation study that the proposed method achieves good performance for time series whether changing abruptly or smoothly. The superiority to the other existing methods is also investigated. An application to longitudinal vibration data of the containership provides a wave-approach angle range, which should be recommended when sailing under a harsh sea condition.

1. Introduction

Recently, spectral estimation of stationary multivariate time series has received increased interest both in statistics (Dai and Guo, 2004; Rosen and Stoffer, 2007; Beran and Heiler, 2009; Krafty and Collinge, 2013) and in engineering (Ramponi et al., 2009; Ferrante et al., 2012). However, as in the univariate case, many multivariate time series are nonstationary, and hence estimating their time-varying spectra can provide us some insights into physical processes that generate these time series. For instance, with continuous changes of loading conditions (low or high draft and trim) and wave conditions (speed, sea state and heading), wave-induced vibrations of the hull girder of a ship are time-varying. The wave-induced fatigue damage of the hull girder comes mainly from two sources. One is sudden vibration, which is referred to as whipping and may be excited by nonlinear impulsive wave loads such as bow flare-, stem-, bottom- or stern slamming. The other is resonance vibration, which is referred to as springing and may be excited by oscillating wave loads. These two types of vibrations can be detected by analyzing marginal spectra and cross-spectra of multivariate vibration time series. Therefore, it is of great practical interest to estimate the time-varying multivariate spectra to figure out the laws of the wave-induced loads of the hull girder.[1]

Similar to the univariate case (Rosen et al., 2012), this article proposes a methodology for analyzing possibly nonstationary multivariate time series by adaptively dividing the time series into an unknown but finite number of segments

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[1] A supplementary file (see Appendix C), containing several figures, a guidance of R programs and some sampling steps that were omitted for reason of space, is available as an electronic annex to this article, as are R programs implementing the proposed algorithm.

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and estimating the corresponding local spectra by smoothing splines. By adopting the Bayesian framework, our estimation utilizes smoothing-stochastic approximation Monte Carlo (SSAMC) methods. Given a segmentation of the time series, the likelihood function is approximated via a product of the local Whittle likelihoods. Thus, no parametric assumption is imposed on the time series data. Both the number of segments and the length of each segment are assumed unknown and may change from one SSAMC iteration to another.

There are several well-known assumptions for nonstationary univariate time series. One is the piecewise autoregressive (AR) models (Kitagawa and Akaike, 1978; Davis et al., 2006); another is the slowly varying processes such as locally stationary processes defined in Dahlhaus (1997), and time-varying AR processes in which parameters are allowed to vary slowly with time (Adak, 1998). The nonstationary assumption of Rosen et al. (2012) is that conditional on the location and number of segments, the time series is piecewise stationary and the spectrum for each segment is smooth. But the location and number of segments are not pre-specified. Since the model assumption of Rosen et al. (2012) is quite general and applicable to almost all the afore-mentioned nonstationary models, we follow their model assumption and generalize it to the multivariate case.

There has been a great deal of literature reviewed by Rosen et al. (2012) on spectral estimation of nonstationary univariate time series. For stationary multivariate time series, by smoothing the Cholesky decomposition of a multi-taper spectral estimator, Dai and Guo (2004) constructed the spectral estimator from the smoothed Cholesky components. The spectral estimator proposed by Rosen and Stoffer (2007) was also reconstructed from the smoothed Cholesky decomposition components. However, a Bayesian frame using Markov chain Monte Carlo techniques was set up to fit smoothing splines to each component of the Cholesky decomposition of the spectral matrix. Beran and Heiler (2009) considered estimation of the regression cross-spectrum based on periodograms. In their estimation, the conception of nonparametric regression cross-spectrum that was introduced by Beran and Heiler (2008) was employed. Krafty and Collinge (2013) introduced a penalized likelihood approach to nonparametric multivariate spectral analysis through minimizing a penalized Whittle negative loglikelihood. In the engineering, Ferrante et al. (2012) proposed a new spectral estimation technique by employing a multivariate version of the Itakura–Saito distance. Ramponi et al. (2009) described a matricial Newton-type algorithm designed to solve the multivariate spectrum approximation problem.

Although there exist such many researches concerning spectral estimation of multivariate time series, spectral estimation for nonstationary multivariate time series still needs to be developed further due to its complexity. According to our knowledge, based on the SLEX (smooth localized complex exponential) transform, Ombao et al. (2001) (ORvSM) proposed a nonparametric spectral estimator of the bivariate nonstationary time series. By applying a time-varying eigenvalue–eigenvector decomposition of the SLEX spectral density matrix, Ombao et al. (2005) (OvSG) took into account the coherence between all components simultaneously and generalized the method of Ombao et al. (2001) to multivariate time series. For the univariate case, Guo et al. (2003) extended the work of Ombao et al. (2001) to allow for simultaneous smoothing in both the time and frequency domains, and Qin and Wang (2008) used the basic method of Guo et al. (2003) and focused on applying it to analysis of the EEG time series. With the same procedure of Guo et al. (2003), Guo and Dai (2006) (GD) proposed to estimate the spectra of a multivariate locally stationary process by extending the Cholesky decomposition approach (Dai and Guo, 2004). Our method is the improved multivariate version of the procedure of Rosen et al. (2012) (SSAMC versus RJMCMC) and methods of ORvSM, OvSG and GD are analogues or extensions of Guo et al. (2003). Therefore, the superiority of the proposed method to those of ORvSM, OvSG and GD can be at least given by three important aspects just as Rosen et al. (2012) had mentioned on the superiority of their method to that of Qin and Wang (2008).

As is known by many researchers, the Metropolis–Hastings (M–H) algorithm (Metropolis et al., 1953; Hastings, 1970) and the Gibbs sampler (Geman and Geman, 1984) are prone to get trapped into local energy minima in simulations from a system in which the energy landscape is rugged. The likelihood function of the paper is a product of unknown but finite number of approximate Whittle likelihoods, which are obtained by dividing the time series into segments. Since both the number of segments and the locations of partition points are unknown and to be determined, the problem should be classified as model selection. To overcome the local-trap problem of model selection, many advanced Monte Carlo algorithms have been proposed, for example, Liang (2009) and other references therein. Due to the self-adjusting mechanism, the stochastic approximation Monte Carlo (SAMC) (Liang et al., 2007) is successful and outperforms the reversible jump Markov Chain Monte Carlo (RJMCMC) (Green, 1995) for the model selection problem in sample space exploration when the model space is complex. By inserting a smoothing step into each iteration, Liang (2009) proposed a new algorithm called the smoothing-SAMC (SSAMC). Since the numerical results of Liang (2009) show that the SSAMC outperforms both the SAMC and the RJMCMC, we employed the SSAMC scheme in this paper. Each MCMC iteration of Rosen et al. (2012) consists of two types of moves, within-model moves and between-model moves. However, each SSAMC iteration of ours consists of κ samples and each sample is drawn from three types of moves—birth, death and simultaneous.

This article is organized as follows. Sections 2 and 3 present the models, priors and sampling schemes for stationary and nonstationary multivariate time series, respectively. Section 4 indicates the performance of the proposed method by several simulation examples, and Section 5 provides the methodology with analysis of the bivariate ship hull vibration data. Section 6 contains our concluding remarks.