Common oscillatory modes in geomagnetic activity, NAO index and surface air temperature records

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Abstract

Detection and extraction of quasi-oscillatory dynamical modes from instrumental records of geophysical data became a useful tool in analysing variability of observed phenomena reflected in complex, multivariate geophysical signals. Using the extension of the Monte Carlo Singular System Analysis (MC SSA), based on evaluating and testing regularity of dynamics of the SSA modes against the colored noise null hypothesis, we demonstrate detection of oscillatory modes with period about 96 months in the long-term records of aa index as well as in the records of surface air temperature from several mid-latitude European locations and in the North Atlantic Oscillation index.

Key words: geomagnetic activity, Monte Carlo Singular System Analysis, oscillatory mode, North Atlantic Oscillation, climate variability, solar-terrestrial relations

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1 Introduction

Possible influence of the solar variability on the climate change have been the subject of research for many years, however, there are still open questions and unsolved problems (for reviews, see e.g. Rind (2002); Bard & Frank (2006); Kane (2005)). Probably the longest historical record of the solar variability are the so-called sunspot numbers. In the middle of the 19th century it was discovered by a druggist H. Schwabe that the number of spots on the Sun varied in a cyclic manner with a characteristic time about 11 years. After the sunspot numbers, aa index, the time series characterizing the geomagnetic activity, provides the longest data set of solar proxies which goes back to 1868 (Mayaud, 1972). Since there are no direct measurements of solar irradiance available until the beginning of the 1980's, the data of geomagnetic variations are used for additional study of solar activity, especially of irradiance. The long-term trend of irradiance is supposed to be inferred by taking account of the magnetic activity record. The amplitude antipodal activity index aa exhibits an 11-yr cycle superimposed on a long-term background (Mayaud, 1972; Lean et al., 1995). General similarity in time variations of the Earth's surface temperature and the low frequency component of the aa index over the last 120 years indicates a significant role of solar variability in climate change. Two-fold increase of the solar magnetic flux was noted (Cliver et al., 1998).

The role of the geomagnetic activity in the climate change became a topic theme of many recent studies. Close relations during the last sixty years were found between the geomagnetic activity and the surface air temperature (Bucha & Bucha, 1998; Ponyavin, 2004; Gao et al., 2004; Valev, 2006), winds distributions (Bochníček & Hejda, 2006) and tropospheric circulation characterized by the NAO index (Lukianova & Alekseev, 2004; Bochníček & Hejda, 2005).

A number of studies indicate substantial increase of geomagnetic activity during the last century and especially from the 1940s (Cliver et al., 1998; Lockwood et al., 1999; Clilverd et al., 2002; Ponyavin, 2004; Lukianova & Alekseev, 2004; Echer et al., 2004; Galet et al., 2005; Le Mouel et al., 2005; Valev, 2006). Some authors (Mursula et al., 2004; Svalgaard et al., 2004; Lean et al., 2005) reanalyzed the long-term geomagnetic activity presented by the aa index. Their results confirm the centennial increase in the global geomagnetic activity which, however is smaller than the two-fold one indicated by Cliver et al. (1998). Another test of a long-term trend using a reconstructed aa index (Clilverd et al., 2005) demonstrated high consistency with the official aa index and supported the idea of long-term increase in the solar coronal magnetic field strength.

Some of the studies have compared the period of high solar and geomagnetic activity during the last sixty years with the reconstructed activity in past millenia and have claimed that such high solar activity is unusual (Usoskin et al., 2003, 2004, 2006) or that several periods with similar activity level have been revealed (Muscheler et al., 2005).

No generally accepted mechanism is known for the explanation of tropospheric responses to the effects of the geomagnetic activity. In order to understand, model, and predict complex, possibly nonlinear processes, it is necessary to identify dynamical mechanisms underlying phenomena reflected in experimental data. The first step of the research in this direction is an attempt to detect trends, oscillatory processes and/or other potentially deterministic signals in a noisy environment. Paluš and Novotná (1998, 2004) have introduced so called enhanced Monte Carlo Singular System Analysis (MC SSA), based on evaluating and testing regularity of dynamics of the SSA modes against the colored noise null hypothesis, in addition to the test based on variance (eigenvalues). The application of the regularity index, computed from a coarse-grained estimation of mutual information, enhances the test sensitivity and reliability in detection of relatively more regular dynamical modes than those obtained by decomposition of colored noise, in particular, in detection of irregular oscillations embedded in the red noise. This enhanced MC SSA was successfully applied in detection of oscillatory modes with a period about 8 years in records of monthly mean near-surface air temperature from several European locations, as well as in the monthly North Atlantic Oscillation index (Paluš & Novotná, 2004).

In this paper we continue and refine the enhanced MC SSA of monthly mean near-surface air temperature from several European locations and the monthly North Atlantic Oscillation index and we add the enhanced MC SSA of the aa index and sunspot numbers time series. The identified oscillatory modes, especially those found in the aa index, are compared with the oscillatory modes extracted from the temperature data and the NAO index.

A brief introduction into the Monte Carlo singular system analysis and its enhancement is given in Sec. 2. The analyzed data are described in Sec. 3. Section 4 summarizes the application of the enhanced MC SSA to the monthly NAO index, near-surface temperature records, the aa index and the sunspot data. Discussion and conclusion are given in Sec. 5.

2 Monte Carlo singular system analysis

Singular system (or singular spectrum) analysis (SSA) in its original form (also known as principal component analysis, or Karhunen-Loève decomposition) is a method for the identification and distinction from noise of important information in multivariate data. It is based on an orthogonal decomposition of a covariance matrix of multivariate data under study. SSA provides an orthogonal basis onto which the data can be transformed, thus making individual data components ("modes") linearly independent. Each of the orthogonal modes (projections of the original data onto new orthogonal basis vectors) is characterized by its variance, which is given by the related eigenvalue of the covariance matrix.

Here we will deal with a univariate version of SSA in which the analyzed data is a univariate time series and the decomposed matrix is a time-lag covariance matrix, i.e., instead of several components of multivariate data, a time series and its time-lagged versions are considered. This form of SSA, which has frequently been used in the field of meteorology and climatology (Vautard & Ghil, 1989; Ghil & Vautard, 1991; Keppenne & Ghil, 1992; Yiou et al., 1994; Allen & Smith, 1994), can provide a decomposition of the studied time series into orthogonal components (modes) with different dynamical properties, and thus "interesting" phenomena such as slow modes (trends) and regular or irregular oscillations (if present in the data) can be identified and retrieved from the background of noise and/or other "uninteresting" non-specified processes.

In traditional SSA, the distinction of "interesting" components (signal) from noise is based on finding a threshold (jump-down) to a "noise floor" in a sequence of eigenvalues given in a descending order. This approach might be problematic if the signal-to-noise ratio is not sufficiently large, or the noise present in the data is not white but "colored." For such cases, statistical approaches utilizing Monte Carlo simulation techniques have been proposed (Ghil & Vautard, 1991; Vautard et al., 1992) for reliable signal/noise separation. The particular case of Monte Carlo SSA (MC SSA) that considers "red" noise, usually present in geophysical data, has been introduced by Allen & Smith (1996).

Now, we present a few necessary details of the SSA method in the form of a technical recipe:

Take the analyzed time series $\{y(i)\}$, $i = 1, \dots, N_0$, and construct a map ("embedding") into a space of n-dimensional vectors $\mathbf{x}(i)$ with components $x^k(i)$, given as

$$x^k(i) = y(i + k - 1), \tag{1}$$

where $k = 1, \dots, n$; and n is the embedding dimension.

Construct a symmetric $n \times n$ matrix $\mathbf{C} = \mathbf{X}^T\mathbf{X}$, with elements:

$$c_{kl} = (1/N)\sum_{i=1}^{N} x^k(i)x^l(i), \tag{2}$$

where $1/N$ is the proper normalization and the components $x^k(i)$, $i = 1, \ldots, N$, are supposed to have a zero mean. The symmetric matrix $\mathbf{C}$ can be decomposed as

$$\mathbf{C} = \mathbf{V}\Sigma\mathbf{V}^T, \tag{3}$$

where the $n \times n$ matrix $\mathbf{V} = \{v_{ij}\}$ gives an orthonormal basis in the space of vectors $\mathbf{x}(i)$, Σ=diag$(\sigma_1, \sigma_2, \ldots, \sigma_n)$, σ_i are non-negative eigenvalues giving the variance of orthogonal modes

$$\xi^k(i) = \sum_{l=1}^{n} v_{lk}x^l(i), \tag{4}$$

into which the original series can be decomposed. For more details, see, e.g., (Vautard et al., 1992).

Of course, the original time series $x^k(i)$ can be reconstructed from the modes, as

$$x^k(i) = \sum_{l=1}^{n} v_{kl}\xi^l(i). \tag{5}$$

In equation (5), the modes $\xi^k(i)$ can also be interpreted as time-dependent coefficients and the orthogonal vectors $\mathbf{v}_k = \{v_{kl}\}$ as basis functions, usually called the empirical orthogonal functions (EOFs).

The clear signal/noise distinction based on the eigenvalues $\sigma_1, \sigma_2, \ldots, \sigma_n$ can only be obtained in particularly idealized situation when the signal/noise ratio is large enough and the background consists of white noise. In many geophysical processes, however, so-called "red" noise with power spectrum of the $1/f$ type is present (Allen & Smith, 1996). Its SSA eigenspectrum also has the $1/f$ character, i.e., an eigenspectrum of the red noise is equivalent to a coarsely discretized power spectrum, where the number of frequency bins is given by the embedding dimension n. The eigenvalues related to the slow modes are much larger than the eigenvalues of the modes related to higher frequencies. Thus, in the classical SSA approach applied to the red noise, the eigenvalues of the slow modes might incorrectly be interpreted as a (nontrivial) signal, or, on the other hand, a nontrivial signal embedded in red noise might be neglected if its variance is smaller than the slow-mode eigenvalues of the background red noise. Therefore, Allen & Smith (1996) proposed comparing the SSA spectrum of the analyzed signal with SSA spectra of a red-noise model fitted to the studied data. Such a red-noise process can be modeled by using an AR(1) model (autoregressive model of the first order):

$$u(i) - \hat{u} = \alpha(u(i-1) - \hat{u}) + \gamma z(i), \tag{6}$$

where $\hat{u}$ is the process mean, α and γ are process parameters, and $z(i)$ is Gaussian white noise with a zero mean and a unit variance.

In order to correctly detect a signal in the red noise, the following approach has been proposed (Allen & Smith, 1996):
First, the eigenvalues are plotted not according to their values, but according to a frequency associated with a particular mode (EOF), i.e., the eigenspectrum in this form becomes a sort of a (coarsely) discretized power spectrum in general, not only in the case of red noise (when the eigenspectrum naturally has this form, as mentioned above).
Second, an eigenspectrum obtained from studied data is compared, in a frequency-by-frequency way, with eigenspectra obtained from a set of realizations of an appropriate noise model (such as the AR(1) model (6)), i.e., an eigenvalue related to a particular frequency bin obtained from the data is compared with a range of eigenvalues related to the same frequency bin, obtained from the set of realizations of the chosen AR(1) model.

The detection of a nontrivial signal in an experimental time series becomes a statistical test in which the null hypothesis that the experimental data were generated by a chosen noise model is tested. The realizations of the considered noise model ("null hypothesis"), i.e., the artificial data generated by the chosen noise model, are usually called "surrogate data" (Theiler et al., 1992; Allen & Smith, 1996; Paluš, 1995; Paluš & Novotná, 2004). When an eigenvalue associated with some frequency bin differs with a statistical significance from the range of related noise model eigenvalues, then one can infer that the studied data cannot be fully explained by the null hypothesis and could contain an additional (nontrivial) signal.

The above MC SSA is a sophisticated technique, but it still assumes that the signal of interest has been linearly added to a specified noise background and therefore that the variance in the frequency band, characteristic of the signal, is significantly greater than the typical variance in this frequency band obtained from the noise model. If the studied signal has a more complicated origin, e.g., when an oscillatory mode is embedded into a background process without significantly increasing variance in a particular frequency band, the standard MC SSA can fail. In order to be able to detect any interesting dynamical mode independently of its (relative) variance, Paluš & Novotná (2004) have proposed testing also dynamical properties of the SSA modes against the modes obtained from the surrogate data. In their particular implementation, the dynamics of the modes is characterized by their predictability (or regularity) measured by means of information theory.

The mutual information $I(X;Y)$ of two random variables X and Y is given by $I(X;Y) = H(X) + H(Y) - H(X,Y)$, where the entropies $H(X)$, $H(Y)$, $H(X,Y)$ are defined in the usual Shannonian sense (Cover & Thomas, 1991). For a time series $\{x(t)\}$, considered as a realization of a stationary and ergodic stochastic process $\{X(t)\}$, $t = 1, 2, 3, \ldots$, we compute the mutual information $I(x(t); x(t+\tau))$ as a function of time lag τ. In the following, we will mark $x(t)$ as x and $x(t+\tau)$ as x_τ, i.e. we evaluate $I(x;x_\tau)$. Let us find such τ_{max} that for $\tau' \geq \tau_{max}$: $I(x;x_{\tau'}) \approx 0$ for the analyzed datasets. Then we define the regularity index to be the norm of the mutual information:

$$||I(x;x_\tau)|| = \frac{\Delta\tau}{\tau_{max} - \tau_{min} + \Delta\tau} \sum_{\tau=\tau_{min}}^{\tau_{max}} I(x;x_\tau) \tag{7}$$

with $\tau_{min} = \Delta\tau = 1$ (sample) as a usual choice.

Since the mutual information $I(x;x_\tau)$ measures the average amount of information contained in the process $\{X\}$ about its future τ time units ahead, the regularity index $||I(x;x_\tau)||$ gives an average measure of predictability of the studied signal and is inversely related to the signal's entropy rate, i.e., to the rate at which the system, or process, producing the studied signal "forgets" information about its previous states (Paluš, 1996).

Finally, we realize the enhanced MC SSA as follows:

(1) The studied time series undergoes SSA as briefly described above, or, in detail in (Paluš & Novotná, 2004), i.e., using an embedding window of length n, the $n \times n$ lag-correlation matrix $\mathbf{C}$ is decomposed using the SVDCMP routine (Press et al., 1986). In the eigenspectrum, the position of each eigenvalue on the abscissa is given by the dominant frequency associated with the related EOF, i.e., detected in the related mode. That is, the studied time series is projected onto the particular EOF, the power spectrum of the projection (mode) is estimated, and the frequency bin with the highest power is identified. This spectral coordinate is mapped onto one of the n frequency bins, which equidistantly divide the abscissa of the eigenspectrum.
(2) An AR(1) model is fitted to the series under study, and the residuals are computed.
(3) The surrogate data are generated using the above AR(1) model, where "scrambled" (randomly permutated in temporal order) residuals are used

as innovations, i.e., the noise term $\gamma z(i)$ in (6) .

(4) Each realization of the surrogates undergoes SSA as described in step 1. Then, the eigenvalues for the whole surrogate set, in each frequency bin, are sorted and the values for the 2.5th and 97.5th percentiles are found. In eigenspectra, the 95% range of the surrogates' eigenvalue distribution is illustrated by a horizontal bar between the above percentile values.

(5) For each frequency bin, the eigenvalue obtained from the studied data is compared with the range of the surrogate eigenvalues. If an eigenvalue lies outside the range given by the above percentiles, the null hypothesis of the AR(1) process is rejected, i.e., there is a probability $p < 0.05$ that the data can be explained by the null noise model.

(6) For each SSA mode (a projection of the data onto a particular EOF), the regularity index is computed, as well as for each SSA mode for all the realizations of surrogate data. The regularity indices are processed and statistically tested in the same way as the eigenvalues. The regularity index is based on mutual information obtained by a simple box-counting approach with marginal equiquantization (Paluš, 1995, 1996, 1997a).

3 The data

The NAO index is traditionally defined as the normalized pressure difference between the Azores and Iceland. The NAO data used here and their description are available at `http://www.cru.uea.ac.uk/cru/data/nao.htm`.

In the initial stage of this study, we used monthly average near-surface air temperature time series from ten European stations, see (Paluš & Novotná, 2004) for details; obtained from the Carbon Dioxide Information Analysis Center Internet server (`ftp://cdiac.esd.ornl.gov/pub/ndp041`) and a time series from the Prague–Klementinum station from the period 1781 – 2002. The long-term monthly averages were subtracted from the data, so that the annual cycle was effectively filtered out. In near future, further analyses will include data from other stations as well as from NCEP/NCAR reanalysis series.

The aa-index is defined by the average, for each 3-hour period, of the maximum of magnetic elements from two near-antipodal mid-latitude stations in Australia (Melbourne) and England (Greenwich). The data spanning the period 1868–2005 were obtained from World Data Centre for Solar-Terrestrial Physics, Chilton, `http://www.ukssdc.ac.uk/data/wdcc1/wdc_menu.html`.

The sunspot data has been obtained from the internet address `http://sidc.oma.be/DATA/monthssn.dat` due to the SIDC-team, Royal Observatory of Belgium, Ringlaan 4, 1180 Brussels, Belgium.

4 Enhanced MC SSA detection of oscillatory modes: The results

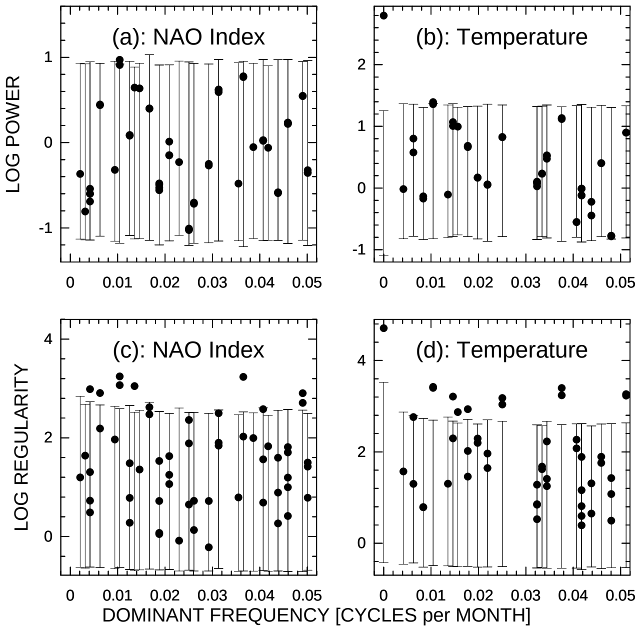

Fig. 1. Enhanced MC SSA of the monthly NAO index (a,c) and monthly average near-surface air temperature series (Prague–Klementinum station) (b,d). Low-frequency parts of eigenspectra – logarithms of eigenvalues ("LOG POWER") (a,b) and regularity index spectra (c,d). Bursts – eigenvalues or regularity indices for the analysed data; bars – 95% of the surrogate eigenvalues or regularity index distribution, i.e., the bar is drawn from the 2.5th to the 97.5th percentiles of the surrogate eigenvalues/regularity indices distribution. Both datasets span the period 1824–2002, the embedding dimension $n = 480$ months was used.

Figure 1 presents the results from the enhanced MC SSA for the considered NAO index and the monthly average near-surface air temperature time series (Prague–Klementinum station) obtained using the embedding dimension $n = 480$ months. In the standard MC SSA, the only eigenvalue undoubtedly distinct from the surrogate range is the trend (zero frequency) mode in the temperature (Fig. 1b). Further, there are two modes at the frequency 0.0104 just above the surrogate bar in both the temperature and NAO tests (Figs. 1a,b). These results, however, are still "on the edge" of significance and are not very convincing.

A quite different picture is obtained from the analyses based on the regularity index (Figs. 1c,d). Several oscillatory modes have been detected with a high statistical significance. The distinction of the regularity indices of these modes from the related surrogate ranges is clear and even the simultaneous statistical inference (see Paluš (1995) and references therein) cannot jeopardize the significance of the results. The significant modes in the NAO are located at the frequencies (in cycles per month) 0.004, 0.006, 0.0104, 0.014, 0.037 and 0.049, corresponding to the periods of 240, 160, 96, 73, 27 and 20 months, respectively. Besides the zero frequency (trend) mode, the significant modes in the temperature are located at the frequencies 0.0104, 0.014, 0.016, 0.018, 0.025, 0.037 and 0.051, corresponding to the periods of 96, 68, 64, 56, 40, 27 and 20 months, respectively. The modes with the period of 8 years were studied in (Paluš & Novotná, 2004), their mean period was estimated with higher precision as 7.8 years. Besides the latter modes (and the trend mode in the temperature), the highest regularity index was obtained for the modes with the period of 27 months (frequency 0.037). This frequency lies within the range of the quasi-biennial oscillations (QBO) and behaviour of these modes was studied by Paluš & Novotná (2006).

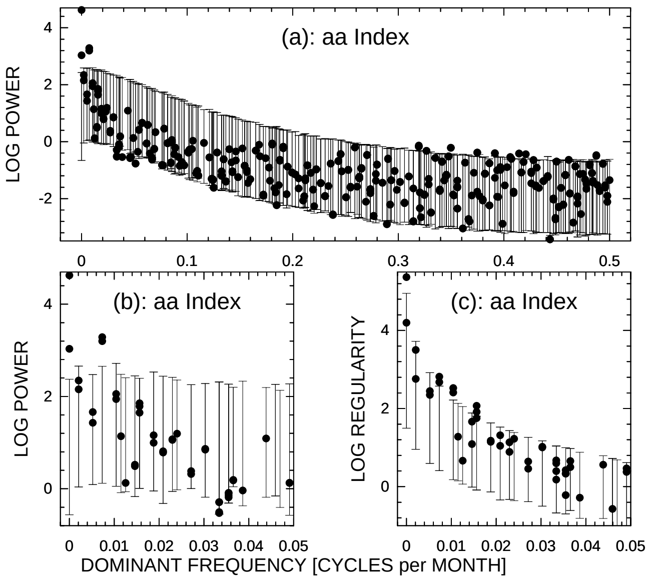

Fig. 2. Standard MC SSA of the monthly aa index – full eigenspectrum (a). Enhanced MC SSA of the monthly aa index (b,c). The low-frequency part of the eigenspectrum – logarithms of eigenvalues ("LOG POWER") (b), and the regularity index spectrum (c). Bursts – eigenvalues or regularity indices for the analysed data; bars – 95% of the surrogate eigenvalues or regularity index distribution, i.e., the bar is drawn from the 2.5th to the 97.5th percentiles of the surrogate eigenvalues/regularity indices distribution. The dataset spans the period 1868–2005, the embedding dimension $n = 480$ months was used.

Figure 2a presents the full eigenspectrum of the aa index and related AR(1) surrogate data. It can be understood as the standard MC SSA. Here we present the full eigenspectrum in order to illustrate the power spectrum of the surrogate red noise, depicted by the vertical bars, since, as it was stated above, the eigenspectrum of the red noise is a discretized version of its power spectrum, with the number of frequency bins given by the used embedding dimension. The enhanced MC SSA consists of both the eigenspectrum (Fig. 2a,b) and the regularity index spectrum (Fig. 2c). Since in this study we concentrate on slow oscillatory modes, in Figs. 2b,c we present the low frequency parts of the eigenspectrum and the regularity index spectrum in the same way as in the case of the temperature and NAO index above. In the standard (eigenvalue)

Source	Period [months]				
data	136	120	96	64	27
sunspots	+	+	−	−	−
aa	+	−	+	+	−
T	−	−	+	+	+
NAO	−	−	+	−	+

Table 1
Occurrence of the most significant oscillatory modes with periods of approximately 136, 120, 96, 64 and 27 months in the four source data: sunspot numbers, aa index, average near-surface air temperature and NAO index.

analysis of the aa index (Fig. 2b) we can see significant modes for the trend, i.e., the zero frequency mode, and for the mode on the frequency 0.0073 which corresponds to the period of 136 months, i.e. to the 11-year solar activity cycle. The analysis based on the regularity index (Fig. 2c) confirms the previous two modes and adds two more ones on frequencies 0.0104 and 0.016 corresponding to the periods of 96 and 64 months.

Analyzing the monthly sunspot data, the only clear significance in both the eigenspectrum and the regularity index spectrum is the mode with the period of 136 months. After removal of this mode and subsequent analysis, a significant mode on the closest higher frequency bin occurs. Its period is 120 months. It is important to note that the frequency accuracy of the SSA approach is limited by the number of frequency bins given by the embedding dimension. The accuracy of the frequency or the period of a particular mode can be increased after the extraction of this mode from the original data and its subsequent spectral or autocorrelation analysis, as Paluš & Novotná (1998, 2004) have done for the temperature mode. On the other hand, oscillatory modes from natural processes are never strictly periodic and their frequency is variable. For instance, the period of the sunspot cycle varies between 9 and 13 years. (A histogram of the instantaneous frequencies of the sunspot cycle can be found in (Paluš et al., 2007), Fig. 5b). Therefore, the periods given here should be understood as limited accuracy estimates of an average period of a particular mode.

The common occurrence of the oscillatory modes with the periods of approximately 136, 120, 96, 64 and 27 months in the sunspot numbers, the aa index, the near-surface air temperature and the NAO index is summarized in Tab. 1. The mode with the period of 96 months or 8 years has been detected in the three of the five analyzed data sources, i.e. in the atmospheric temperature, in the NAO index and in the aa index. The time series of the modes

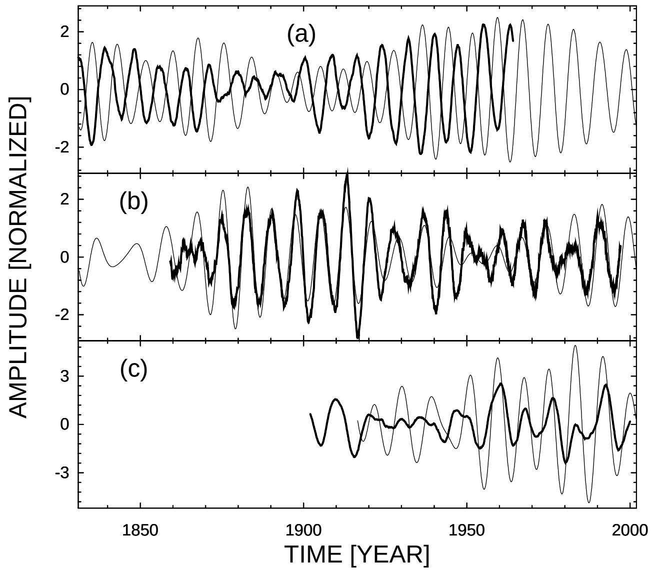

Fig. 3. The oscillatory modes with the mean period 96 moths extracted by using SSA (thick lines) and CCWT (thin lines) from the near-surface air temperature (a), the NAO index (b), and the aa index (c).

extracted by using the SSA, i.e., by projecting the input data on the particular EOF, are presented in Fig. 3 by thick lines, and compared with the modes obtained by using the complex continuous wavelet transform (CCWT) (Torrence and Compo, 1998) with the central wavelet frequency set to the period of 96 months (thin lines in Fig. 3). Using the SSA, there is an uncertainty of timing of the modes given by the embedding window, and a part of the data equal to the embedding window is lost. We positioned the SSA modes by maximizing the crosscorrelation between the mode and the original data. This approach, however, not always gives unambiguous results. Thus the SSA mode and the wavelet mode, obtained from the temperature data (Fig. 3a) are shifted by π (a half of the period), otherwise their agreement is very good. The timing of the SSA and CCWT modes from the NAO index (Fig. 3b) is consistent, however, the wavelet transform performs stronger smoothing. In the modes from the aa index (Fig. 3c) the CCWT mode is smoother and slightly shifted in time in comparison with the SSA mode.

It is interesting to note that the oscillatory mode with the period of 7.8 years has been detected in the NAO, in the Arctic Oscillation (AO), in the Uppsala winter surface atmospheric temperature, as well as in the Baltic Sea ice annual maximum extent by Jevrejeva & Moore (2001). Unal & Ghil (1995) and Jevrejeva et al. (2006) observed oscillations with periods 7 – 8.5 years in a number of sea level records. Feliks & Ghil (2007) report the significant oscillatory mode with the 7.8 year period in the Nile River record, Jerusalem precipitation, tree rings and in the NAO index. Our first application of the enhanced MCSSA (Paluš & Novotná, 1998) yielded the observation of the mode with the period 7.8 years in near-surface atmospheric temperature from several European locations. Recently, the enhanced MCSSA analyses of the temperature data were refined and the analysis of the NAO index was added (Paluš & Novotná, 2004). In this paper the number of processes containing the oscillatory mode with the approximate period of 8 years was extended by the geomagnetic activity aa index.

5 Discussion and Conclusion

In this paper, Monte Carlo Singular System Analysis has been extended by evaluating and testing the regularity of the dynamics of the SSA modes against the colored noise null hypothesis in addition to the test based on variance (eigenvalues). The nonlinear approach to the measurement of regularity and predictability of the dynamics, based on a coarse-grained estimate of the mutual information, increases the MC SSA test sensitivity and reliability in the detection of dynamical modes which are relatively more regular than those obtained by decomposition of colored noise.

The enhanced MC SSA has been applied to records of monthly average near-surface air temperature from several European locations, to the monthly NAO index, as well as to the monthly aa index and the monthly sunspot numbers. Several significant oscillatory modes have been detected in all the source data, some of them with common periods (Tab. 1). While the QBO 27-month mode is shared by the atmospheric data, the period 136 months mode, related to the solar activity cycle is shared by the sunspot data and the aa index, the mode with the period of 64 months, or approximately 5.5 yr has been detected in the aa index and in the temperature records. The mode with the period of 96 months or 8 years is present in the three data sources, i.e. in the atmospheric temperature, in the NAO index and in the aa index. These findings give a solid basis for further research of relations among the dynamics reflected in the analysed data and thus between the geomagnetic activity and the climate variability. The existence of oscillatory modes opens the possibility to apply the recently developed synchronization analysis (Pikovsky et al., 2001; Paluš, 1997b) which already has found successful applications in studies of relations between atmospheric phenomena. Maraun & Kurths (2005) discovered epochs of phase coherence between El Niño/Southern Oscillation and Indian monsoon, while Paluš & Novotná (2006) demonstrated phase synchronization or phase coherence between the above mentioned QBO modes extracted from the temperature and the NAO index. The analysis of instantaneous phases of oscillatory processes allows to detect very weak interactions (Pikovsky et al., 2001) and also causality relations if one oscillatory process drives the other one (Rosenblum & Pikovsky, 2001; Paluš & Stefanovska, 2003). In such analysis, Mokhov & Smirnov (2006) have demonstrated that the NAO interacts, or is influenced by the other global atmospheric oscillatory process – the El Niño

Southern Oscillation. We believe that the synchronization analysis will help to uncover mechanisms of the tropospheric responses to the geomagnetic activity and to contribute to better understanding of the solar-terrestrial relations and their role in the climatic change.

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