A NEW METHOD FOR NORTH-SOUTH ASYMMETRY OF SUN SPOT AREA ANALYSIS

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ABSTRACT

We have studied the temporal variation in the North-South asymmetry of the sunspot area during the period from 1874 to 2007. Though the 9-year periodicity is commonly reported, shorter periodicities is still under study. We employ the cepstrum analysis method to analyze the noisy power spectrum of the North-South asymmetry. We demonstrate that the *cleaned* power spectrum shows reduction of the spurious background noise level. Some of short period peaks in the power spectrum disappear after deconvolution. It should be, however, pointed out that power spectrum might look less noisy because of a filtering process during deconvolution. We conclude by pointing out that a more sophisticate filtering algorithm is required to produce a precise and reliable periodicity estimate.

Keywords: sun: sunspot – methods: data analysis

1. INTRODUCTION

Periodic behaviors of the solar activity have been widely known for a long time and well studied in great details (e.g., Schwabe 1843, Carrington 1860). One of the most interesting properties of the solar activity is its North-South asymmetry. On the basis of various solar activity features, significant North-South asymmetries were revealed and confirmed. Consequently, it is very important to analyze the behavior of the solar activity separately for the two hemispheres to understand its nature and underlying mechanism. The North-South asymmetry of the solar activity has been the subject of many studies carried out using different features of solar activity (Roy 1977, White & Trotter 1977, Swinson, Koyama, & Saito 1986, Vizoso & Ballester 1989, 1990, Schlamminger 1991, Yi 1992, Carbonell, Oliver, & Ballester 1993, Verma 1987, 1993, Oliver & Ballester 1994, Krivova & Solanki 2002, Li et al. 2002, Vernova et al. 2002, Temmer, Veronig, & Hanslmeier 2002, Ballester, Oliver, & Carbonell 2005, Berdyugina & Usoskin 2003, Ichimoto et al. 1985, Ataç & Özgüç 1996, 2001, Li, Schmieder, & Li 1998, Temmer et al. 2001, Waldmeier 1971, Özgüç & Ücer 1987, Tritakis, Petropoulos, & Mavromichalaki 1988, Gigolashvili et al. 2005, Antonucci, Hoeksema, & Scherrer 1990, Mouradian & Soru-Escaut 1991, Knaack, Stenflo, & Berdyugina 2004, 2005, Javaraiah & Gokhale 1997, Gigolashvili, Japaridze, & Kukhianidze 2005, Javaraiah & Ulrich 2006, Zaatri et al. 2006).

In this paper, we explore the periodicity of the North-South asymmetry by employing the cepstrum analysis method. For determining reliably a precise period is crucial in providing an insight of the North-South asymmetry of solar activity. Recently, Chang (2007a) reported (1-5)-year periodicities in the noisy power spectrum of the North-South asymmetry, as well as the 9-year periodicity which corresponds definitely to the main peak in the power spectrum. Shorter periodicities in the solar activity need to be confirmed by an independent method since they may have some implications on the solar dynamo mechanism.

The cepstrum method is a very powerful tool to obtain information out of noisy data. This analyzing technique is used in many fields of physics and engineering, such as, acoustics, geophysics, helioseismology, image processing, etc (e.g., Baudin, Gabriel, & Gilbert 1993 and references therein). We have applied this method, for the first time, to the observed sunspot area in the northern and southern solar hemispheres.

This paper begins with descriptions of the analysis method in section 2. We present the data set we have used in this work in section 3. We present and discuss results, and finally conclude in section 4.

2. CEPSTRUM

Periodical occurrences are computed by applying the periodogram analysis method by Lomb and Scargle (e.g., Press et al. 1992), which is particularly appropriate for the analysis of unevenly-spaced data. This analysis method is basically same as Fourier analysis and sine curve fitting analysis. A typical way of analyzing periodic signals is to utilize the Fourier transform, which is defined by

$$\hat{S}(\nu) = \int S(t) \exp(-i2\pi\nu t) dt, \tag{1}$$

where S(t) is the signal as a function of time t and ν is the cyclic frequency. This method results in the harmonic contents of the signal. The problem of the Fourier transform is that it is suited for stationary data, which is not the general case. Hence, one may require a homomorphic deconvolution of the noise and the signal to suppress effects due to the noise. By doing so one may wish to obtain true information. One of these deconvolutions was first developed by an electronic engineer (Oppenheim 1965), who was usually facing the signal which was the sum of the damped sine wave and the randomly distributed spiky noise. Since the nature of data is similar, this approach was used by geophysicists who have echoes in their signal because of reflections on geological layers (e.g., Ulrych 1971).

The method can be divided into three stages: discrimination, filtering, and reconstruction. The discrimination of the two parts (signal and noise) of data is made after some mathematical manipulation of the Fourier transform of the data set. The filtering is perhaps the most critical, since at this stage there is an elimination of unwanted noise and one must be sure that the required information remains in the observed data. The final stage is merely a reversal of the first stage in order to recover the required part of the signal.

2.1 Discrimination

The signal is commonly multiplicate such that the observed data S(t) can be represented by

$$S(t) = O(t) \cdot E(t) \tag{2}$$

where O(t) is the oscillatory signal and E(t) is the randomly distributed noise. The first step for the discrimination is rather classical. That is, it is the Fourier transform of the signal:

$$\hat{S}(\nu) = \hat{O}(\nu) * \hat{E}(\nu) \tag{3}$$

Next, we take the complex logarithm of the Fourier transform:

$$\log \hat{S}(\nu) = \log \hat{O}(\nu) + \log \hat{E}(\nu). \tag{4}$$

The following step is very important since this is where the two functions are discriminated. This is the computation of the inverse Fourier transform of the result above. This is what is called the cepstrum:

Cepstrum =
$$\mathcal{F}^{-1} \log \hat{S}(\nu)$$
, (5)

where

$$\mathcal{F}^{-1}\log\hat{S}(\nu) = \mathcal{F}^{-1}\log\hat{O}(\nu) + \mathcal{F}^{-1}\log\hat{E}(\nu) \tag{6}$$

This cepstrum is a real function (imaginary part equal to zero), and describes the variation of the "maplitude" versus the "quefrency", which has the dimension of time (Bogert, Healey, & Tukey 1963). As their names suggest, those quantities are *not* physical. Now, O and E are separated. Generally speaking, the contribution of O is at very low quefrency with very high values of maplitude, while E spreads at all quefrencies but with very low maplitude.

2.2 Filtering

The issue of this step is how to remove the unwanted noise without eliminating the required information. The first thing one may do is of course to choose which part of the signal to be reconstructed and simply to replace rest parts by zeros. As we point out above, since the real information is concentrated at very low quefrency, a very simple solution can be used: cutting off the maplitude at high quefrency and substituing zeroes. If the signal is very noisy, however, there is no choice. In this case the determination of the cutoff quefrency could be a critical problem. There is no well-known trade-off. Therefore, it is impossible to discriminate the information from the noise. Another way to achieve the filtering is to make an average of the cepstrum of several samples of the time series. Or one may chop the data set into several subsets. For each sample, the information is the same, but the noise may be different. So the contribution of the noise will cancel out while the contribution of the information will stay. In that way, one can be sure that no information about the information is thrown away. In practice the most sensible choice is this. In this particular work, we adopt the second approach.

2.3 Reconstruction

The reconstruction of the signal is simply a reverse process in order to obtain the temporal behavior of the oscillating function, or to get the information in the frequency domain. In either case, following an excursion into a strange mathematical domain, the result is something familiar in the temporal or in the frequency domain.

3. DATA

We have taken recently updated data from the NASA website¹, which is managed by Hathaway and his colleagues in Marshall Space Flight Center. We have used for the present analysis the Greenwich sunspot group data during the period from 1874 to 1976, and the sunspot group data from the Solar Optical Observing Network (SOON) of the US Air Force (USAF)/ US National Oceanic and Atmospheric Administration (NOAA) during the period of from 1977 to 2007. The Royal Greenwich Observatory (RGO) in England has collected and compiled daily sunspot observations from a small network of observatories to produce a dataset of daily observations starting in May of

¹http://solarscience.msfc.nasa.gov/greenwich.shtml

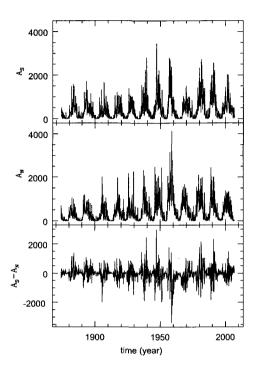


Figure 1. Monthly average of the sunspot area appeared in the solar southern and northern hemispheres, A_S and A_N , and its absolute difference for the period of 1874 - 2007.

1874. The Royal Greenwich Observatory has quit maintaining this dataset in 1976 when the US Air Force started compiling data from its own Solar Optical Observing Network. This compilation has been continued with the help of the US National Oceanic and Atmospheric Administration with much of the same information being compiled through to the present. These derived data include the correction factor of 1.4 for data after 1976 (e.g., Javaraiah 2007). The entire sunspot dataset is available as ASCII text files containing records for individual years. Each file consists of records with information on individual sunspot groups for each day that sunspots were observed. Text files containing the monthly averages of the daily sunspot areas (in units of millionths of a hemisphere) are also available.

In Figure 1, we show monthly average of the sunspot area appeared in the solar northern and southern hemispheres, A_N and A_S , and its difference, $A_S - A_N$, for the period of 1874 - 2007 as a function of time. We analyze the absolute difference instead of a conventional asymmetry index, that is, the difference normalized by the sum, $(A_S - A_N)/(A_S + A_N)$, as used in recent studies (e.g., Yi 1992, Ballester, Oliver, & Carbonell 2005).

One may characterize the sunspot area with random noise superposed on a slowly varying background. The underlying part of sunspot area data is assumed to represent a sum of undamped oscil-

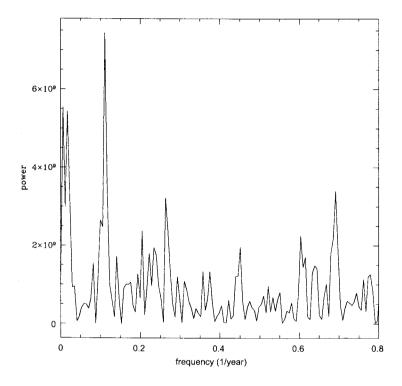


Figure 2. Power spectrum of the difference between monthly average of the sunspot area of northern hemisphere and southern hemisphere for the period of 1874 - 2007. The horizontal axis represents the frequency in unit of 1/year and the vertical axis represents the power in arbitrary unit.

lators. According to the JWKB approximation a solution of the wave equation is given as

$$A_n(t) \propto \omega_n(t)^{-1/2} \sin\{\int \omega_n(t')dt'\},\tag{7}$$

or

$$A_n(t) \simeq A_{n,0} [1 - \frac{\eta}{2\omega_{n,0}} f(t)] \sin\{\omega_{n,0} + \eta f'(t) + \phi_n dt'\}.$$
 (8)

Even though the amplitude function slowly varies over the timescale of a couple of hundreds and the duration of the solar cycle differ a bit, we assume these variations are insignificant (e.g., $\eta \approx 0$) so that their magnitudes are insensitive to our conclusions. Thus, the sunspot area in two hemispheres, A_S and A_N , can be approximated by

$$A_S = (1 + \epsilon_S) \times \sin^n(\omega_0 t + \phi),$$

$$A_N = (1 + \epsilon_N) \times \sin^m \omega_0 t,$$
(9)

where ω_0 represents the solar cycle frequency, ϕ is the phase shift, ϵ_S and ϵ_N are random noise. In the context of the method we present in this paper, effects of ϵ_S and ϵ_N are to be filtered. In

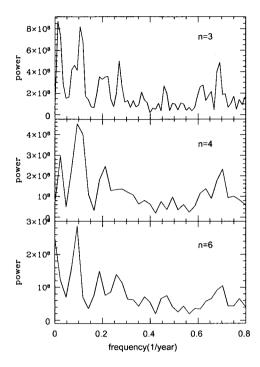


Figure 3. Power spectra of the same data, except that power spectra are resulted after deconvolution using the cepstrum technique. The horizontal axis represents the frequency in unit of 1/year and the vertical axis represents the power in arbitrary unit. The number of subsets to average in the filtering process are denoted in the right upper corner of the panels.

another work it is demonstrated that this representation is a good approximation of the sunspot area asymmetry (e.g., Chang 2007b)

4. RESULTS AND DISCUSSION

In Figure 2, we show the power spectrum (based on the traditional Lomb-Scargle algorithm) of the absolute difference between monthly average of the sunspot area appeared in the solar northern and southern hemispheres, for the period of 1874-2007. The horizontal axis and the vertical axis represent the frequency in unit of 1/year and the power in arbitrary unit, respectively. The most significant peak corresponds to the periodicity of ~ 9 years. Note that the main periodicity of asymmetry does not coincide with the solar ~ 11 year cycle. One may wish to compare our results with those resulted from conventional asymmetry index, that is, the difference normalized by the sum, $(A_S - A_N)/(A_S + A_N)$. The main periodicity of the asymmetry index corresponds to instead ~ 12 years. Interestingly enough, there are also noticeable short periodicities in our power spectrum other than the 9 year periodicity in the asymmetry of the sunspot area, e.g., $\sim 5.0, \sim 3.6, \sim 2.2, \sim 1.6, \sim 1.4$ years.

In Figure 3, we show the *cleaned* power spectra after deconvolution using the cepstrum technique. The horizontal axis and the vertical axis represent the frequency in unit of 1/year and the power in arbitrary unit, respectively. The *cleaned* power spectra show reduction of the spurious background noise. As it is expected, resulting power spectra become less noisy. To filter the noise part of the data we divide the whole data set into 3, 4, 6 shorter pieces and average corresponding cepstra. The recovering process is straightforward. The number of subsets are denoted in the upper right corner of the panels. It is shown that as the number of averaging cepstra increases the obtained power spectrum becomes less noisy. It is, however, pointed out that they might simply look less noisy partly because the spectral resolution degrades as the number of subsets increases (therefore the length of the subset decreases). It is hard to tell whether a truncation is necessary in the filtering stage. According to our preliminary results some improvements are expected when two criteria are simultaneously used in the filtering stage. Once a more sophisticated and automated filtering algorithm is successfully employed a precise and reliable periodicity estimate can be achieved. It can be a complement method of other method such as wavelet analysis (e.g., Chang 2006).

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