Variations in sound pressure levels under random change of atmospheric conditions

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ABSTRACT

Variations in sound power of many environmental noise sources have certain limits. Changes in the environmental conditions also evoke deviations in the measured sound pressure levels within certain boundaries. A span of the possible changes in the noise levels associated with a particular noise source is normally less for consequent time intervals. Its limits can be established from feasible changes of atmospheric conditions and sound power of the source. Measured sound pressure levels (SPLs) of a noise source represent a sequence of probable magnitudes that vary within certain limits. In some cases, variations of the SPLs can be treated as a Markov chain and respectively be explored using statistical methods. It is shown that under certain assumptions the random noise contribution variations tend to be periodic. Conclusions about character of signal from source of interest can be obtained from measurements when the source controls the total noise. Information about the SPLs variations can be utilised for data analysis aiming to calculate noise contribution from a particular noise source. Analysis of data pertained to monitoring of wind farm noise is considered as a case study. The suggested technique can be engaged to extract wind farm noise from SPL logging data without employment of special instruments or excessively complex procedures. If necessary, it can be adopted for other applications.

INTRODUCTION

Contribution from a noise source at a distant receiver depends on characteristics of noise source itself and environmental factors such as wind speed and direction, temperature, humidity, atmospheric turbulence etc (Harris, 1998, CONCAWE, 1981, International Organization for Standardization, 1996). Sound level meters and conventional logging instruments report total noise, which also includes ambient noise contribution. In some cases, such as monitoring of noise from wind farms at a distant receiver, it is impractical to employ start/stop method which involves switching the noise source on and off to identify its contribution. Also, ambient noise can be comparable or greater than the contribution from the source of interest. It is possible to assume the character of variations of noise from the source, taking into account the acoustic specification of the noise source and possible variations of environmental conditions. Statistical methods can be utilised to study variations in the source noise and calculate its contribution. This paper demonstrates one of the possible approaches to analysing the contribution from a distant source using a statistical approach and wavelet decomposition technique.

VARIATIONS IN CONTRIBUTION OF A NOISE SOURCE AT A DISTANT RECEIVER

Let us consider a noise source with a sound power which may vary within certain limits that may be derived from the technical specification. Other environmental factors such as atmospheric temperature, humidity, pressure, wind speed and direction will influence noise propagation from the source to a stationary receiver. It is possible to derive a span of possible fluctuations of the noise source contribution due to the environmental factors assuming limits in their deviations. ISO9613-2 (International Organization for Standardization, 1996) and CONCAWE (CONCAWE, 1981) are widely used for predicting environmental noise propagation and can be utilised for establishing boundaries of possible variations in the noise source contribution due to environmental factors. Consideration of consequent time intervals during a relatively short period generally reduces the span of the possible variations in noise contribution. Also, an assumption that a landscape, barrier effect will not influence changes in the noise level of interest is expected to be valid for many practical situations. For a relatively short time period, variations in the wind speed and direction are major environmental factors affecting fluctuation in the contribution from the noise source (Lenchine, Holmes, 2011).

It has to be noted that we consider contributions from a particular noise source and variations in the total noise levels may be significantly higher due to other noise sources.

Environmental noise contributions and Markov chain

Let us assume that the sound power of a source changes in a random way between maximum and minimum levels and variations in the atmospheric parameters cause changes in the noise contribution at a distant receiver within certain limits from L_{min} to L_{max}. Considering the technical specification of the noise source and the effects of the environmental factors, it is possible to establish limits of variations during the data acquisition interval, from one possible noise contribution to another, as ΔL_{max}. It is then possible to assume that the next value of the source contribution depends on the previous magnitude and the next probable value in a time interval will be within the ΔL_{max} limit from the previous magnitude. A set of possible magnitudes, with corresponding probabilities can be represented as a Markov chain (Grinstead, Snell, 1998, Norris, 1998). Figure 1 shows an example of where the magnitude can attain one intermediate magnitude between the previous state and $L_i \pm \Delta L_{max}$ with equal transition probabilities. This is chosen for the purpose of simplicity. Minimal variation in the noise level can be chosen from an accuracy or practicability perspective. The Markov chain in Figure 1 also demonstrates events where the magnitude after each of the time intervals can not be exactly the same as in the previous state. This assumption is valid for many practical tasks where noise levels measured for 1/8 or 1/10s or smaller intervals always vary due to environmental factors, sound power changes or reporting settings (rounding of results).

The matrix of transition probabilities for the proposed scenario can be derived in the form (Grinstead, Snell, 1998, Norris, 1998):

$$\mathbf{P}=\begin{bmatrix} 0 & 1/(n+1) & 1/(n+1) & ... & 0 & 0 \\ 1/(n+2) & 0 & 1/(n+2) & 1/(n+2) & ... & 0 \\ 1/(n+3) & 1/(n+3) & 0 & ... & ... & 0 \\ ... & ... & ... & 0 & ... & ... \\ 0 & ... & ... & 1/(n+2) & 0 & 1/(n+2) \\ 0 & 0 & ... & 1/(n+1) & 1/(n+1) & 0 \end{bmatrix}, \quad (1)$$

where n is the number of intermediate points between $L_i \pm \Delta L_{max}$. $\mathbf{P}$ is a square matrix with size m×m, where m is the number of discrete values under consideration including L_{min} and L_{max}.

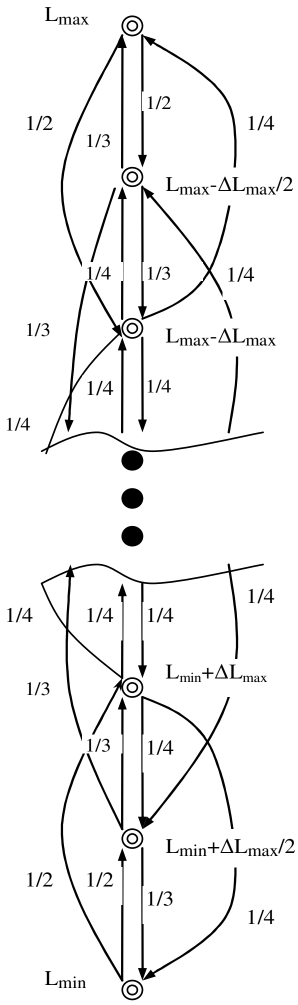


Figure 1. An example of random variations in the noise contribution that can be represented as a Markov chain

For example, if we consider states with 3 intermediate magnitudes between minimum and maximum noise levels, where during one time interval the noise can change in either $\Delta L_{max}/2$ or ΔL_{max} (similar to Figure 1), the transition matrix takes form:

$$\mathbf{P}=\begin{bmatrix} 0 & 1/2 & 1/2 & 0 & 0 \\ 1/3 & 0 & 1/3 & 1/3 & 0 \\ 1/4 & 1/4 & 0 & 1/4 & 1/4 \\ 0 & 1/3 & 1/3 & 0 & 1/3 \\ 0 & 0 & 1/2 & 1/2 & 0 \end{bmatrix}. \quad (2)$$

A Markov chain with the transition matrix (1) is ergodic since it is possible to get from any state to any other state (not necessarily in one step). The ergodic chain has a fixed row probability vector. Magnitudes of the fixed vector can be interpreted as a proportion of times in particular state (Grinstead, Snell, 1998, Norris, 1998). It can be shown that a fixed probability vector corresponding to the transition matrix (1) can be represented as follows:

$$\mathbf{w}=[w_1 \quad ... \quad w_{m/2} \quad w_{m/2+1} \quad ... \quad w_m],$$

where are two maximum values at $w_{m/2}$ and $w_{m/2+1}$ for even m numbers and one maximum at $w_{(m+1)/2}$ for odd m numbers. For example, a fixed probability vector corresponding to the transition matrix (2) has the form:

$$\mathbf{w}=[1/7 \quad 3/14 \quad 2/7 \quad 3/14 \quad 1/7].$$

Minimum probabilities correspond to the extreme SPL magnitudes and the maximum probability is for the middle of the range. It can be shown that increasing the number of intermediate points influences relative magnitudes in the fixed vector:

$$\lim_{m\to\infty}(w_i)=w_{\max},$$

where probabilities w_i do not correspond to L_{min} or L_{max} and w_{max} . Also it is possible to write:

$$\text{if } m\to\infty \text{ or } n\to 1, \text{ then } w_{\max}/w_{\min}\to 2. \quad (3)$$

One of the mathematical interpretations of inverse magnitudes of the fixed probability vector is the average time of recurrence (Grinstead, Snell, 1998, Norris, 1998). Conditions (3) mean that if one considers a Markov process with fine resolution (many intermediate magnitudes) and with a limited ability of significant variations in comparison with the previous state from statistical perspective, the average time when noise from the source equals the same intermediate magnitude will be about 2 times less than it takes for L_{min} or L_{max}. A periodic variation meets such sort of requirement.

Shape of the noise level variations

It was shown in the previous section that for a large number of data acquisition intervals and under accepted assumptions, noise contribution from the source tends to vary with a periodic pattern. This, however, still does not give us ideas about the shape of the periodic variation. If variations of sound power of the source are periodic, it may then be assumed that shape of the noise level changes is approximately the same as if it were measured at the source. Another methodology that can be utilised to work out generic variations associated with a noise source of interest is by making SPL measurements at the receiver when noise is controlled by the source.

For instance, monitoring of wind farm noise can be performed firstly close to a turbine to detect the shape of the SPL variations, and secondly at the receiver when environmental conditions are favourable and wind farm noise is clearly audible.

Implications of noise monitoring with multiple sources providing similar noise contribution

Tasks of compliance checking may be very difficult in cases where background noise is comparable with contributions from the source of interest. In a quiet rural environment the start/stop method may not be practicable as it does not lead to notable changes in the measured noise levels. Options for implementation of correlation analysis may be also limited. For example, if one considers a wind farm monitoring task, noise from trees, bushes and atmospheric turbulence is correlated with the wind farm since it is connected with the wind speed. In many situations wind speeds at the wind farm site and at the receiver are correlated to some degree therefore it is not possible to accept hypothesis about statistical independence of the noise sources in general. Background noise may also have similar frequency content which makes choice of possible methods for the contribution separation limited.

WAVELET ANALYSIS FOR CALCULATING NOISE FROM A DISTANT RECEIVER

Wavelet of a periodic signal

A signal measured at a distant receiver may contain components from different noise sources that can be partially coherent. Wavelet analysis technique frequently is employed for denoising of complex signals or where the ratio of signal of interest energy to energy of other sources is subtle (Prek, 2004, Prokofiev, Lenchine and Shakhmatov, 2006).

In many practical situations the source of interest may have similar frequency content and be coherent with the noise of other sources, however shape of the signal from the source of interest can be assumed unique.

Wavelet transformation is a tool which enables representation of the original signal as the sum of scaled and shifted mother functions ψ (Goswami, Chan, 1999, Hernandes, Weiss, 1996, Shumaker, Webb, 1993):

$$x(t) = \sum_k C_k \psi_k(t). \tag{4}$$

To determine the wavelet coefficients C the mother wavelet is scaled, shifted and checked for correlation with the part of the signal. Therefore it is a convenient tool to use for comparison of the signal with assumed shape of the signal of interest.

As it is discussed in the previous sections, from a statistical perspective, consequent variations of noise levels caused by different environmental factors should be periodic. For the sake of simplicity, we assume that variations in the signal of interest can be approximated by the cosine function:

$$x(t) = A\cos(\omega t),$$

where A is the amplitude and ω is the circular frequency of the signal.

The Modulus of Morlet wavelet represents a sinusoidal Gaussian- based function and can be used for the decomposition of the assumed signal. The Morlet wavelet also is well balanced for frequency and time resolution (see (Goswami, Chan, 1999, Shumaker, Webb, 1993) for a discussion about properties of the wavelet).

The Modulus of Morlet wavelet coefficients $C(a,b)$ for a sine signal can be calculated by the analytical expression (Prokofiev, Lenchine and Shakhmatov, 2006):

$$\left|C(a,b)\right| = A\frac{\sqrt{a}}{2}e^{-f_b(\pi^2 f_c^2 + 0.25a^2\omega^2)} \times \sqrt{e^{2\pi f_c f_b a\omega} + e^{-2\pi f_c f_b a\omega} + 2\cos(2b\omega)}, \tag{5}$$

where a and b are the scale and position of the wavelet respectively, f_c is the centre frequency of Morlet wavelet, f_b is the bandwidth parameter (see example of wavelet modulus for cosine function in Figure 2a).

If total noise measurements contain a cosine signal, the frequency and amplitude can be calculated from the wavelet of the time history using a system of equations (4) for particular combinations of a and b parameters.

A phase of the Morlet wavelet for cosine function can be found as follows:

$$\varphi(a,b) = \operatorname{atan}\left(\frac{e^{\pi f_b f_c a\omega}\sin[b(\frac{2\pi f_c}{a} - \omega)] + e^{-\pi f_b f_c a\omega}\sin[b(\frac{2\pi f_c}{a} + \omega)]}{e^{\pi f_b f_c a\omega}\cos[b(\frac{2\pi f_c}{a} - \omega)] + e^{-\pi f_b f_c a\omega}\cos[b(\frac{2\pi f_c}{a} + \omega)]}\right). \tag{6}$$

It may be more convenient to find parameters of the cosine function using simplified expressions. At $a > 0.7/(f_c f_b)$ the formula for the modulus of the wavelet coefficient can be simplified (Prokofiev, Lenchine and Shakhmatov, 2006) to:

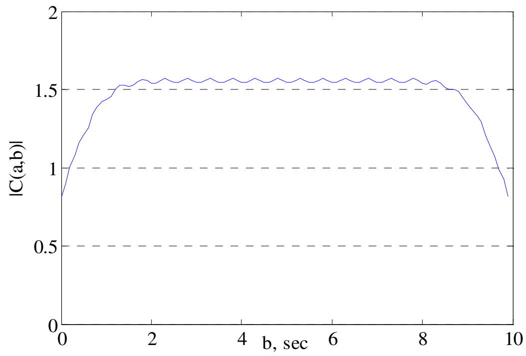
$$\left|C(a,b)\right| \approx A\frac{\sqrt{a}}{2}e^{-f_b(\pi f_c - 0.25a\omega)^2}. \tag{7}$$

An expression for the phase of the Morlet wavelet can also be simplified for sufficiently high wavelet scales neglecting second terms in the numerator and denominator of expression (6). Then the phase can be approximately calculated by the formula:

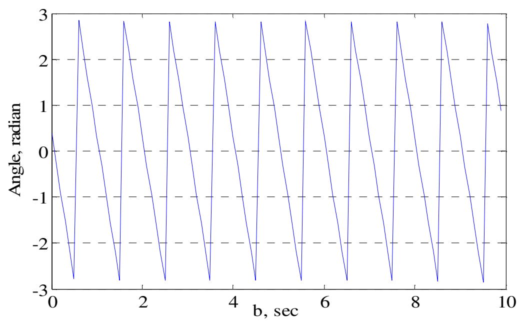
$$\varphi(a,b) \approx b(\frac{2\pi f_c}{a} - \omega).$$

Normally the phase is represented in accordance with accepted convention (for example from $-\pi$ to π), therefore a phase instead of an infinite linear increase for a fixed scale a, may look like a sawtooth or triangle function (Figure 2b).

The phase dependence gives us an option to calculate the frequency of the cosine signal as the inverse of the phase period. Then the amplitude of the signal can be found from expression (7). It should be noted that since the analysed signal is not infinitely long, the border distortion effect influence the calculation of the wavelet coefficients (Hernandes, Weiss, 1996, Shumaker, Webb, 1993). To improve the accuracy of the calculations it is advised to take the wavelet coefficients which correspond to the periodic signal frequencies (ridge of the wavelet) and with offset from the beginning and end of the analysed time interval. Preliminary information about the possible frequency of the signal is also useful to choose the centre frequency of Morlet wavelet correctly.



a)



b)

Figure 2. Modulus (a) and phase of wavelet coefficients (b) for 1Hz signal with unity amplitude (Morlet wavelet with centre frequency 1Hz, bandwidth parameter 1Hz, $a=10$, sampling frequency 10Hz)

Calculation of amplitude modulation parameters for wind farm noise

Extraction of noise contributions from wind turbines at a distant receiver can be a difficult task since statutory limits normally are very strict and noise from a wind farm may be comparable or even less than background or extraneous noise. Also, wind farm noise and background may be essentially coherent since they depend on the wind speed. A significant variety of contributing noise sources can make any assumption of the background noise (white, exponential or other type) invalid. Generally wind turbines generate noise in similar frequency bands as natural background and extraneous sources in a rural environment. All of these implications limit applicability of conventional methods that could be engaged for monitoring of wind farm noise where total noise is not controlled by emissions from the wind turbines.

Noise emission from industrial wind turbines possesses one or more noise characteristics such as low frequency content, amplitude modulation or tonality. Normally, amplitude modulation is present to some extent however perception of the character significantly depends on the level of masking noise at the measurement location. Let us assume that variations of the wind farm contributions are still periodic as it is shown in the previous chapter. SPL associated with the wind farm noise should vary with the same dominant frequency as noise measured close to the turbines. Amplitude modulation of wind turbine noise corresponds to the blade pass frequency, which is normally between 0.5 to 1.5Hz for modern 3 blade turbines (Lenchine, 2009).

Figure 3 represents the time history of SPL measured in the vicinity of a wind farm with a sampling interval 0.1s. Time of the record is comparable with the period necessary to accommodate a 1m/s change in the wind speed in the turbine operating regime, therefore the sound power of the turbines is not expected to change significantly during this time interval. The noise levels are affected by background noise, and periodic changes in the levels can hardly be noted at a first glance. The turbines have been operated at 17rpm mode, i.e. the amplitude modulation frequency is around 0.85Hz.

The Morlet wavelet of the SPL is shown in Figure 4 (f_c $=0.85Hz$, $f_b=1Hz$). Scale $a=10$ corresponds to the frequency 0.875Hz, which is nearest to the mean modulation frequency from available scales. The modulus of the wavelet varies over time, which means that the amplitude modulation depth is also not stable since it is affected by the environmental factors and extraneous noise sources. However, the phase of the wavelet is similar to that of a cosine signal with an average period corresponding to the frequency of modulation. One can compare phases in Figure 2b and Figure 5b. The mean estimate of the amplitude of SPL variations at the blade pass frequency can be obtained by formula (7) where the magnitudes affected by the wavelet edge effect should be disregarded (see Figure 5a).

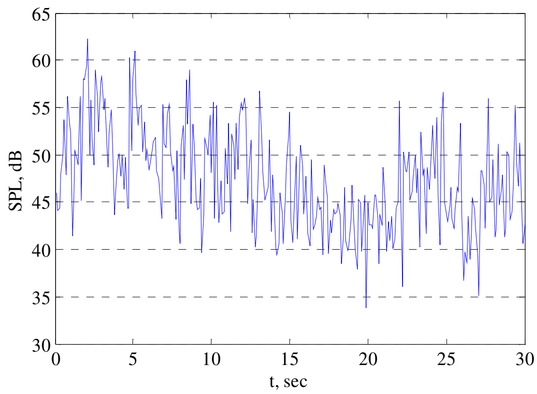


Figure 3. Time history of SPL with contribution from source with amplitude modulation

The estimate of average level difference associated with the amplitude modulation is about 4.4dB. It should be noted that many conventional wavelet algorithms operate with an assumption of unit time spacing between the measurement points. Respectively, real time representation requires scaling of time or wavelet position in $1/f_s$ where f_s is the sampling frequency and frequency ω in the computation formulas must be multiplied by the same factor.

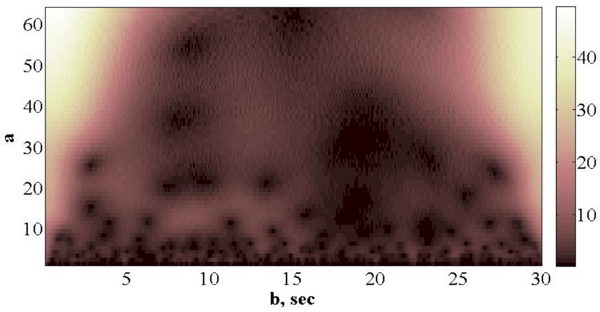
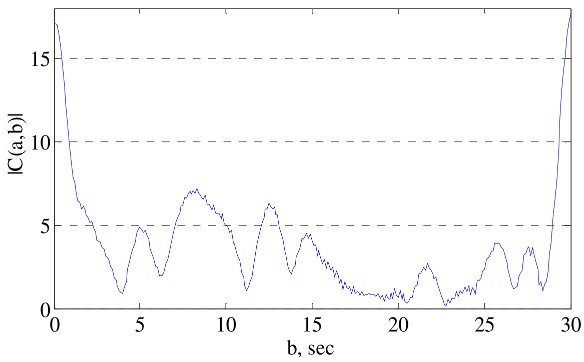


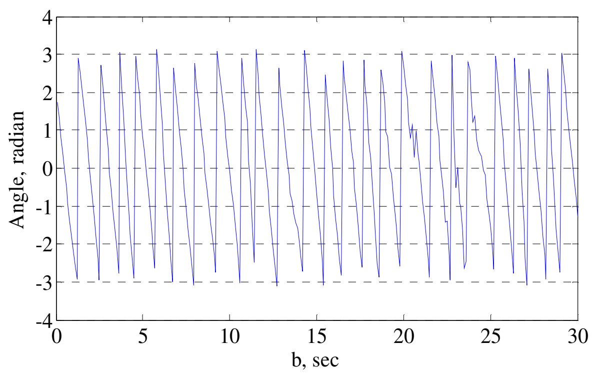
Figure 4. Modulus of Morlet wavelet transform

There are a few other peculiarities of the signal that are not obvious from conventional analysis of the signal. Modulus and phase dependencies at scales *a=32* and *a=47* (correspond to frequencies around *0.27* and *0.19Hz*) also are similar to Figure 2. Their wavelets indicate presence of harmonic components in the signal (see Figure 6). Low frequency oscillations at *a=47* may be caused by the random variations of the environmental parameters as it is explained earlier in the paper. A periodic component at *a*=32 is close to the rotor frequency of the wind turbines.

Estimates of the average SPL variations at these scales give magnitudes a bit above 2dB. Subjective assessment of the sound indicates that amplitude modulation at the blade passing frequency is clearly perceivable. However, none of the lower frequency SPL variations is perceived as a modulation since it is below a perception threshold of 3dB, and relative fluctuation strength decreases for the lower frequencies (Fastl, Zwiker, 2007).



a)



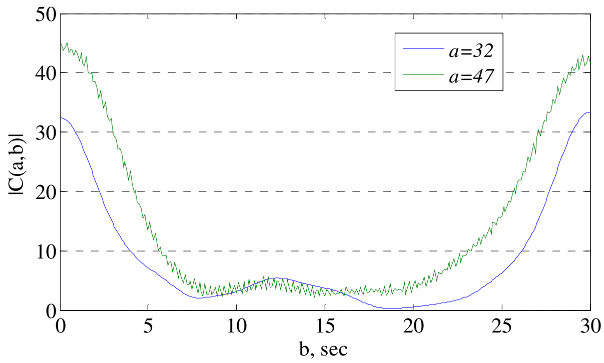
b)

Figure 5. Modulus (a) and phase (b) of the Morlet wavelet at scale *a*=10

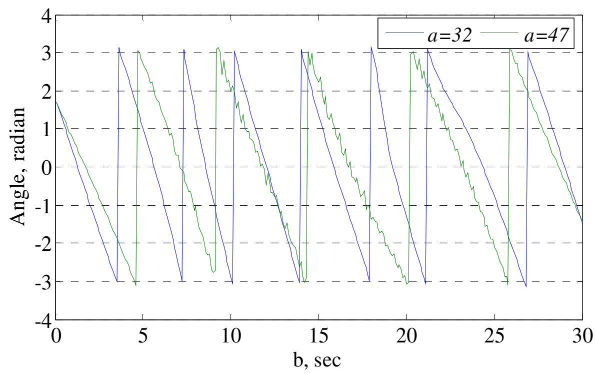
A similar technique, based on the post-process of SPL time histories, where parameters of the source can be considered locally stationary can be used to evaluate amplitude modulation of other sources or variations of SPL caused by random change of environmental factors.

SUMMARY

It is shown that variations of contribution from a distant noise source due to a random change of environmental parameters, or sound power of the source, can be considered as a Markov process from a probability perspective. The contribution variations tend to be periodic and may exhibit features similar to the amplitude modulation. Since a change in the atmospheric conditions should not significantly affect shape of periodic variations of SPL associated with the noise source, it can be engaged in evaluation of the noise impact at a distant receiver where the total noise is influenced by natural background and extraneous noise sources. For example, wavelet analysis of SPL time histories can be performed to assess amplitude modulation associated with wind farm noise, which inherently possesses amplitude modulation at the blade pass frequency. If necessary this modulation can be separated from periodic processes associated with other factors.



a)



b)

Figure 6. Modulus (a) and phase (b) of the wavelet at scales *a*=32 and *a*=47

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