Estimation of the instantaneous harmonic parameters of speech

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1. Introduction

Sinusoidal modelling was introduced in (McAulay and Quateri, 1986) and since then it has been used in many processing applications. The essential feature of the model is efficient representation of tonal quasistationary sounds that constitute significant part of speech and music. Because of that the model has been used in speech-coding systems such as multiband excitation vocoder (D. Griffin and J. Lim, 1988) and transform coder (McAulay and Quateri, 1992) as well as in wideband audio-coding (Levine and Smith, 1998). Sinusoidal representation considers the signal as a combination of sinusoids with slowly-varying amplitudes and frequencies, and therefore is not as efficient for transient and noise sounds. This fact gives rise to hybrid parameterization that implies signal separation into deterministic (quasistationary or periodic) and stochastic components (Serra, 1989). There are two and three-part models that are sines+noise (SN) or sines+transients+noise (STN) respectively. As long as sinusoidal modelling can be applied directly to the input in both cases the stochastic components is often referred to as residual.

Hybrid models give improved performance in high-quality coding using perceptual criteria (Painter and Spanias, 2003) and noise reduction systems. Such parametric representation is also used in audio effects processing (time-scale modifications, enhancement, pitch shifting) and text-to-speech (TTS) synthesis (Dutoit 1997). Speech representation by means of the hybrid approach is of great interest because speech segments of different nature (voiced and unvoiced) conform to different parts of the representation (deterministic and stochastic respectively). The model provides good parameterization of both parts and allows using different processing techniques for them. Voiced speech is often modelled by harmonically related sinusoids (harmonic model) that can significantly reduce number of parameters needed for storage, processing or transmission.

Signal separation into deterministic and stochastic components as well as estimation of sinusoidal parameters is still a fundamental problem of sinusoidal modelling. As a rule estimation accuracy drastically influences overall system performance that accounts for improving analysis techniques. Inaccurate periodic/noise decomposition can add some perceptible artefacts to the signal that cannot be taken away afterwards. The short-term Fourier transform (STFT) is usually used as the main tool for sinusoidal analysis. The signal in that case is assumed to be quasi-stationary that means retaining constant spectral parameters over a period of time. Although some very good results have been reported in speech synthesis (Dutoit 1997) and coding (Spanias 1994), the assumption of stationarity might be a considerable constraint for further development. First of all it is hard to make an adequate parametric representation of unsteady tonal sounds. Another problem is to analyze signals with rapidly changing pitch (for instance STFT is hardly applicable to higher-order harmonics of speech because of their large frequency variations). These issues require alternative methods that could give a more localized description of the signal and a suitable estimation of components with rapid frequency modulations.

As has been reported (Boashash, 1992) there are several alternatives to STFT-based techniques that can provide instantaneous parameters estimation. As long as instantaneous parameters of a monocomponent periodical signal can be easily estimated by discrete energy separation algorithm (DESA) (Maragos et al., 1993) or by Hilbert transform (Hahn, 1996), the general approach to analysis of multicomponent signals is to use narrow-band filtering (Gianfelici et. Al., 2007).

As well as sinusoidal modelling, linear predictive coding (LPC) is a very popular speech processing technique. The main reasons for it can be listed as follows:

- good approximation to the vocal tract spectral envelope (especially for voiced speech);
- source-vocal tract separation;
- simplicity and low computational load.

There are a lot of LPC-related papers that describe parameters estimation, transformation and spectrum analysis (Markel and Gray, 1976); (Rabiner and Juang, 1993). LPC can be very effective in coding applications due to its equivalent line spectral frequencies (LSF) representation that is robust against vector quantization. Additional powerful LPC feature is ability to extract vocal tract parameters that is used for formant tracking. According to the LPC model the source signal is presented as a set of prediction coefficients and an excitation sequence.

The prediction coefficients can be obtained either by the autocorrelation or covariance method (Huang et al., 2001). The main weak point of the methods is parameters averaging within the analysis frame that leads to poor performance for frequency-modulated signals.

As far as sinusoidal and linear prediction models are closely related it is possible to propose a direct conversion of sinusoidal parameters into prediction coefficients in order to get instantaneous LPC representation that might be useful in some speech and audio applications. Bringing all the benefits of instantaneous analysis into LPC model will result in more accurate vocal tract parameters estimation, particularly for segments with unsteady sinusoidal components.

The aim of the chapter is to introduce a method for accurate sinusoidal analysis and give some consideration to applications of the sinusoidal model. The analysis technique is based on the filter with a closed-form impulse response (Azarov et al., 2008). The filter produces an analytical signal at the output providing direct instantaneous parameters estimation. The impulse response of the filter can be adjusted in accordance with the instantaneous pitch contour ensuring appropriate processing of higher-order harmonics. The method of pitch estimation is given as well. In order to evaluate performance of the proposed methods, the technique is applied to speech and audio signals. Although the described techniques are focused mainly on speech processing they are also applicable to wideband audio signals.

Concatenative TTS system was chosen as the primary experimental application, since it demonstrates high flexibility of the sinusoidal modeling and provides insight into the analysis technique at the same time. The chapter also describes estimation of the LPC coefficients from sinusoidal parameters in order to improve prediction accuracy and spectral energy localization for signals with frequency modulations. An explicit parameters conversion technique is given and its performance is compared with well-known autocorrelation and covariance methods.

The chapter is organized as follows. Section 2 gives essentials of the sinusoidal and harmonic modelling. Section 3 describes synthesis of the analysis filter with modulated impulse response. In Section 4 some estimation techniques based on narrow band filtering are presented. The linear prediction model is briefly described and parameters conversion technique is presented in Sections 5 and 6 respectively. Section 7 gives some experimental results of using described harmonic analysis and conversion techniques in speech processing systems.

2. The sinusoidal and harmonic models

The sinusoidal model assumes that the signal $s(n)$ can be expressed as the sum of its periodic and stochastic parts:

$$s(n) = \sum_{k=1}^{K} \mathrm{MAG}_k(n)\cos\varphi_k(n) + r(n), \tag{1}$$

where $\mathrm{MAG}_k(n)$ - the instantaneous magnitude of the k-th sinusoidal component, K is the number of components, $\varphi_k(n)$ is the instantaneous phase of the k-th component and $r(n)$ is the stochastic part of the signal. Instantaneous phase $\varphi_k(n)$ and instantaneous frequency $f_k(n)$ are related as follows:

$$\varphi_k(n) = \sum_{i=0}^{n} \frac{2\pi f_k(i)}{F_s} + \varphi_k(0), \tag{2}$$

where F_s is the sampling frequency and $\varphi_k(0)$ is the initial phase of the k-th component. The harmonic model states that frequencies $f_k(n)$ are integer multiples of the fundamental frequency $f_0(n)$ and can be calculated as:

$$f_k(n) = kf_0(n). \tag{3}$$

The harmonic model is often used in speech coding since it represents voiced speech in a highly efficient way. The parameters $\mathrm{MAG}_k(n)$, $f_k(n)$ and $\varphi_k(0)$ are estimated by means of the sinusoidal (harmonic) analysis. The stochastic part obviously can be calculated as the difference between the source signal and estimated sinusoidal part

$$r(n) = s(n) - \sum_{k=1}^{K} \mathrm{MAG}_k(n)\cos\varphi_k(n). \tag{4}$$

Assuming that sinusoidal components are stationary (i.e. have constant amplitude and frequency) over a short period of time that correspond to the length of the analysis frame, they can be estimated using STFT

$$S(f) = \frac{1}{N}\sum_{n=0}^{N-1} s(n)e^{\frac{-j2\pi nf}{N}}. \tag{5}$$

The transformation gives spectral representation of the signal by sinusoidal components of multiple frequencies. The balance between frequency and time resolution is defined by the length of the analysis frame N. Because of the local stationarity assumption STFT can hardly give accurate estimate of frequency-modulated components, that gives rise to such approaches as harmonic transform (Zhang et al., 2004) and fan-chirp transform (Weruaga and Kepesi, 2007). The general idea of these approaches is using the Fourier transform of the warped-time signal. The signal warping can be carried out before transformation or directly embedded in the transform expression (Weruaga and Kepesi, 2007):

$$S(\omega,\alpha)=\sum_{n=-\infty}^{\infty}s(n)\sqrt{|1+\alpha n|}e^{-j\omega\left(1+\frac{1}{2}\alpha n\right)n}, \quad (6)$$

where ω is frequency and α is the chirp rate. The transform is able to identify components with linear frequency change, however their spectral amplitudes are assumed to be constant.

There are several methods for estimation instantaneous harmonic parameters. Some of them are connected with the notion of analytic signal based on the Hilbert transform (HT). A unique complex signal $z(t)$ from a real one $s(t)$ can be generated using the Fourier transform (Gabor, 1946). This also can be done as the following time-domain procedure:

$$z(t)=s(t)+jH[s(t)]=a(t)e^{j\varphi(t)}, \quad (7)$$

where H is the Hilbert transform, defined as

$$H[s(t)]=p.v.\int_{-\infty}^{+\infty}\frac{s(t-\tau)}{\pi\tau}d\tau, \quad (8)$$

where $p.v.$ denotes Cauchy principle value of the integral. $z(t)$ is referred to as Gabor's complex signal, $a(t)$ and $\varphi(t)$ can be considered as the instantaneous amplitude and instantaneous phase respectively. Signals $s(t)$ and $H[s(t)]$ are theoretically in quadrature. Being a complex signal $z(t)$ can be expressed in polar coordinates, and therefore $a(t)$ and $\varphi(t)$ can be calculated as follows:

$$a(t)=\sqrt{s^2(t)+H^2[s(t)]}, \quad (9)$$

$$\varphi(t)=\arctan\left(\frac{H[s(t)]}{s(t)}\right). \quad (10)$$

Recently the discrete energy separation algorithm (DESA) based on the Teager energy operator was presented (Maragos et al., 1993). The energy operator is defined as:

$$\Psi[s(n)]=s^2(n)-s(n-1)s(n+1), \quad (11)$$

where the derivative operation is approximated by the symmetric difference. The instantaneous amplitude $\mathrm{MAG}(n)$ and frequency $f(n)$ can be evaluated as:

$$\mathrm{MAG}(n)=\frac{2\Psi[s(n)]}{\sqrt{\Psi[s(n+1)-s(n-1)]}}, \quad (12)$$

$$f(n)=\arcsin\sqrt{\frac{\Psi[s(n+1)-s(n-1)]}{4\Psi[s(n)]}}. \quad (13)$$

The Hilbert transform and DESA can be applied only to monocomponent signals as long as for multicomponent signals the notion of a single-valued instantaneous frequency and amplitude becomes meaningless. Therefore the signal should be split into single components before using these techniques. It is possible to use narrow-band filtering for this purpose (Abe et al., 1995).

3. Analysis filter

In voiced speech harmonic components are spaced in frequency domain so that each component can be limited by a narrow frequency band. The harmonic components can be separated within the analysis frame by filters with non-overlapping bandwidths. Therefore proposed method for harmonic parameters estimation can be based on narrow band filtering. The analysis filter, used in this chapter has the following features (Azarov et al., 2008):

- filtering in an arbitrary bandwidth;
- the impulse response is described by a closed form expression (a continuous function of the bandwidth border frequencies);
- estimation of the instantaneous parameters directly from the output signal;
- impulse response adjustment according to frequency modulations of pitch (implicit time warping);
- continuous and smooth contours of estimated parameters $\mathrm{MAG}_k(n)$ and $f_k(n)$.

3.1 Filter synthesis

The filter can be synthesized using the N-point STFT that can be considered as a finite impulse response (FIR) filter for a specified normalized frequency f, producing the stationary sinusoid $\bar{s}(n)$ at the output

$$\bar{s}(n) = \mathrm{MAG}\big(S(f)\big)\cos\left(\frac{2\pi nf}{N} + \varphi\big(S(f)\big)\right). \tag{14}$$

Constant amplitude $\mathrm{MAG}\big(S(f)\big)$ and initial phase $\varphi\big(S(f)\big)$ can be calculated as follows:

$$\mathrm{MAG}\big(S(f)\big) = \sqrt{\mathrm{Re}S(f)^2 + \mathrm{Im}S(f)^2}, \tag{15}$$

$$\varphi\big(S(f)\big) = -\arctan\frac{\mathrm{Im}S(f)}{\mathrm{Re}S(f)}. \tag{16}$$

where Re and Im denote real and imaginary parts respectively. The closed form impulse response $h(n)$ of this filter for frequency f in Hz is:

$$h(n) = \cos\left(\frac{2\pi}{F_s}nf\right). \tag{17}$$

Generalizing this expression we can obtain the impulse response of a filter that produces a band-limited sinusoidal component:

$$h(n) = \frac{\int_{F_1}^{F_2}\cos\left(\frac{2\pi}{F_s}nf\right)df}{F_2 - F_1}, \tag{18}$$

where F_1 and F_2 are limits of the frequency band ($F_1 < F_2$). Integrating of expression (18) leads to the impulse response in the following form:

$$h(n)=\begin{cases}1, & n=0\\ \dfrac{\frac{F_s}{n\pi}\cos\left(\frac{2\pi n}{F_s}F_c\right)\sin\left(\frac{2\pi n}{F_s}F_\Delta\right)}{2F_\Delta} & n\neq 0\end{cases}, \tag{19}$$

where $F_c=(F_1+F_2)/2$ and $F_\Delta=(F_2-F_1)/2$. Parameters F_c and F_Δ correspond to the center frequency of the filter band and the half of bandwidth respectively. The filter output $s_{F_c,F_\Delta}(n)$ can be calculated as the convolution of $s(n)$ and $h(n)$ and can be expressed as the following sum:

$$s_{F_c,F_\Delta}(n)=\sum_{i=0}^{N-1}\frac{s(i)F_s}{2\pi(n-i)F_\Delta}\cos\left(\frac{2\pi(n-i)}{F_s}F_c\right)\sin\left(\frac{2\pi(n-i)}{F_s}F_\Delta\right), \tag{20}$$

The expression can be rewritten as:

$$s_{F_c,F_\Delta}(n)=A(n)\cos(0n)+B(n)\sin(0n), \tag{21}$$

where

$$A(n)=\sum_{i=0}^{N-1}\frac{s(i)F_s}{2\pi(n-i)F_\Delta}\sin\left(\frac{2\pi(n-i)}{F_s}F_\Delta\right)\cos\left(\frac{2\pi(n-i)}{F_s}F_c\right),$$

$$B(n)=\sum_{i=0}^{N-1}\frac{-s(i)F_s}{2\pi(n-i)F_\Delta}\sin\left(\frac{2\pi(n-i)}{F_s}F_\Delta\right)\sin\left(\frac{2\pi(n-i)}{F_s}F_c\right).$$

Thus, considering (21), the expression (20) is a magnitude and frequency-modulated cosine function

$$s_{F_c,F_\Delta}(n)=\mathrm{MAG}(n)\cos(\varphi(n)) \tag{22}$$

with instantaneous magnitude $\mathrm{MAG}(n)$, phase $\varphi(n)$ and frequency $f(n)$ that can be calculated as:

$$\mathrm{MAG}(n)=\sqrt{A^2(n)+B^2(n)}, \tag{23}$$

$$\varphi(n)=\arctan\left(\frac{-B(n)}{A(n)}\right), \tag{24}$$

$$f(n)=\frac{\varphi(n+1)-\varphi(n)}{2\pi}F_s. \tag{25}$$

Instantaneous sinusoidal parameters of the filter output are available at every instant of time within analysis frame. The bandwidth specified by border frequencies F_1 and F_2 (or by parameters F_c and F_Δ) should cover the frequency of the periodic component that is being analyzed. The filter output $s_{F_c,F_\Delta}(n)$ can be converted into the analytical signal $s^a_{F_c,F_\Delta}(n)$ in the following way:

$$s^a_{F_c,F_\Delta}(n)=A(n)+jB(n). \tag{26}$$

3.2 Analysis filter with modulated impulse response

For accurate sinusoidal parameters estimation of periodical components with high frequency modulations a frequency-modulated filter can be used (Petrovsky et al., 1999). The closed form impulse response of the filter is modulated according to frequency contour of the analyzed component. This approach is quite applicable to analysis of voiced speech since rough harmonic frequency trajectories can be estimated from the pitch contour. Considering centre frequency of the filter bandwidth as a function of time $F_c(n)$ the equation (21) can be rewritten in the following form:

$$s_{F_c,F_\Delta}(n) = A(n)\cos(0n) + B(n)\sin(0n) \quad (27)$$

where

$$A(n) = \sum_{i=0}^{N-1} \frac{s(i)F_s}{2\pi(n-i)F_\Delta} \sin\left(\frac{2\pi(n-i)}{F_s}F_\Delta\right)\cos\left(\frac{2\pi}{F_s}\varphi_c(n,i)\right),$$

$$B(n) = \sum_{i=0}^{N-1} \frac{-s(i)F_s}{2\pi(n-i)F_\Delta} \sin\left(\frac{2\pi(n-i)}{F_s}F_\Delta\right)\sin\left(\frac{2\pi}{F_s}\varphi_c(n,i)\right),$$

$$\varphi_c(n,i) = \begin{cases} \sum_{j=n}^{i} F_c(j), & n < i \\ -\sum_{j=i}^{n} F_c(j), & n > i \\ 0, & n = i \end{cases}.$$

The required instantaneous parameters can be calculated using expressions (23)-(25). The frequency-modulated filter has a warped band-pass, aligned to the given frequency contour $F_c(n)$, that provides adequate analysis of periodic components with rapid frequency alterations. This approach is an alternative to time warping that is used in speech analysis (Weruaga and Kepesi, 2007). In Figure 1 an example of parameters estimation is shown. The frequency contour of the harmonic component can be covered by the filter band-pass specified by the centre frequency contour $F_c(n)$ and the bandwidth $2F_\Delta$.

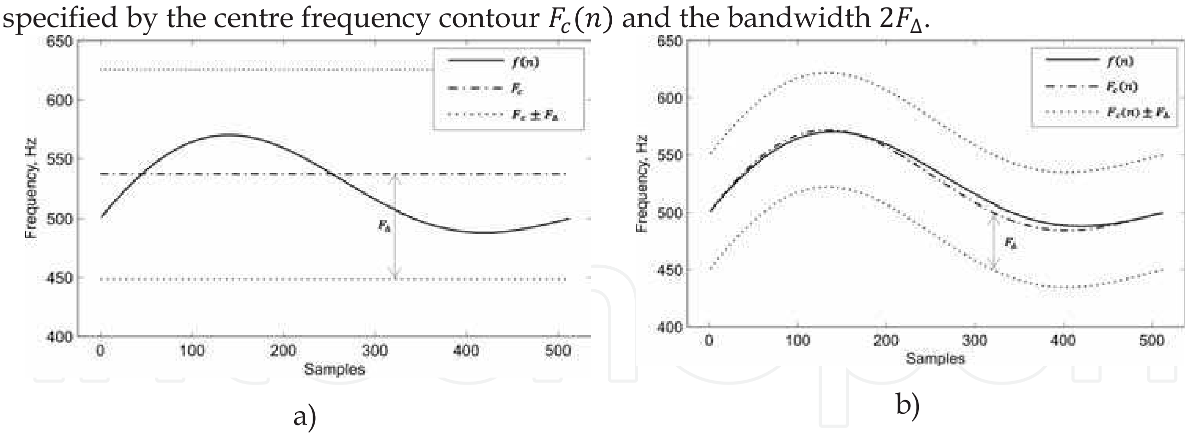


Fig. 1. Short-time analysis using narrow-band filtering ($N = 512$): a) filter with simple impulse response; b) filter with modulated impulse response.

Centre frequency contour $F_c(n)$ is adjusted within the analysis frame providing narrow band filtering of the frequency-modulated component.

4. Estimation techniques

4.1 Sinusoidal analysis

In this subsection the general technique of sinusoidal parameters estimation is presented. The technique does not assume harmonic structure of the signal and therefore can be applied both to speech and audio signals.
In order to locate sinusoidal components in frequency domain the estimation procedure uses iterative adjustments of the filter bands with a predefined number of iterations. At every step the centre frequency of each filter is changed in accordance with the calculated frequency value in order to position energy peak at the centre of the band. At the initial stage the frequency range of the signal is covered by overlapping bands (where h is the number of bands) with constant central frequencies respectively.
At every step the respective instantaneous frequencies are estimated by formulas (21),(23)-(25) at the instant that corresponds to the centre of the frame . Then the central bandwidth frequencies are reset and the next estimation is carried out.
When all the energy peaks are located the final sinusoidal parameters (amplitude, frequency and phase) can be calculated using the expressions (21),(23)-(25) as well. During the peak location process some of the filter bands may locate the same component. Duplicated parameters are discarded by comparison of the centre band frequencies .

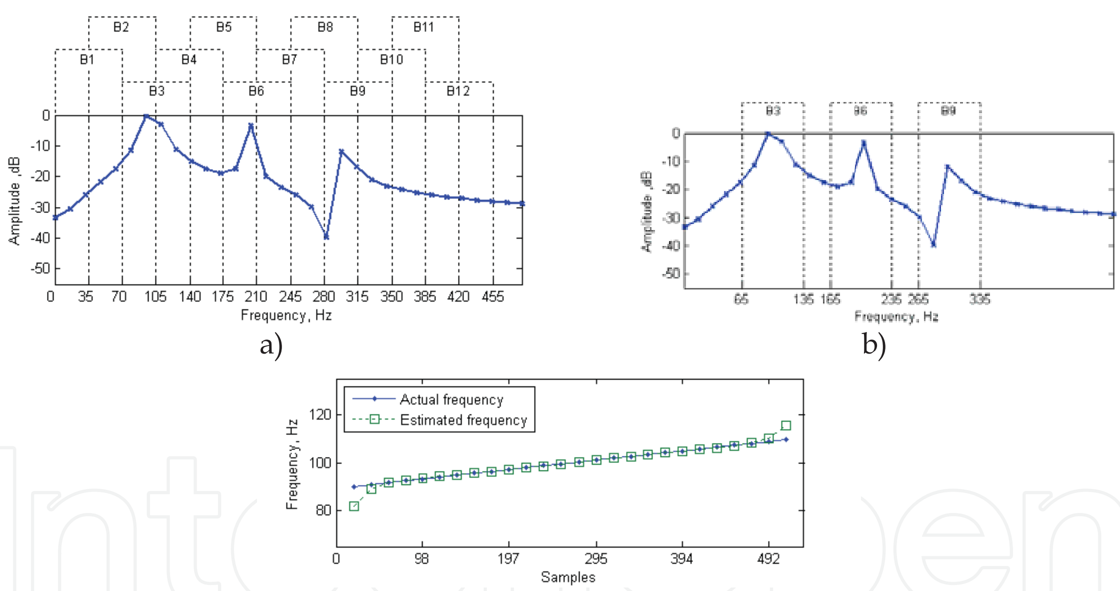


Fig. 2. Sinusoidal parameters estimation using analysis filters: a) initial frequency partition; b) frequency partition after second iteration; c) instantaneous frequency estimation by the analysis filter

In order to discard short-term components (that apparently are transients or noise and should be taken to the residual) sinusoidal parameters are tracked from frame to frame. The frequency and amplitude values of adjacent frames are compared, providing long-term component matching.

The technique has been used in the hybrid audio coder (Petrovsky et al., 2008), since it able to pick out the sinusoidal part and leave the original transients in the residual without any prior transient detection. In Figure 3 a result of the signal separation is presented. The source signal is a bell tune sampled at 44100 Hz (Figure 3(a)).

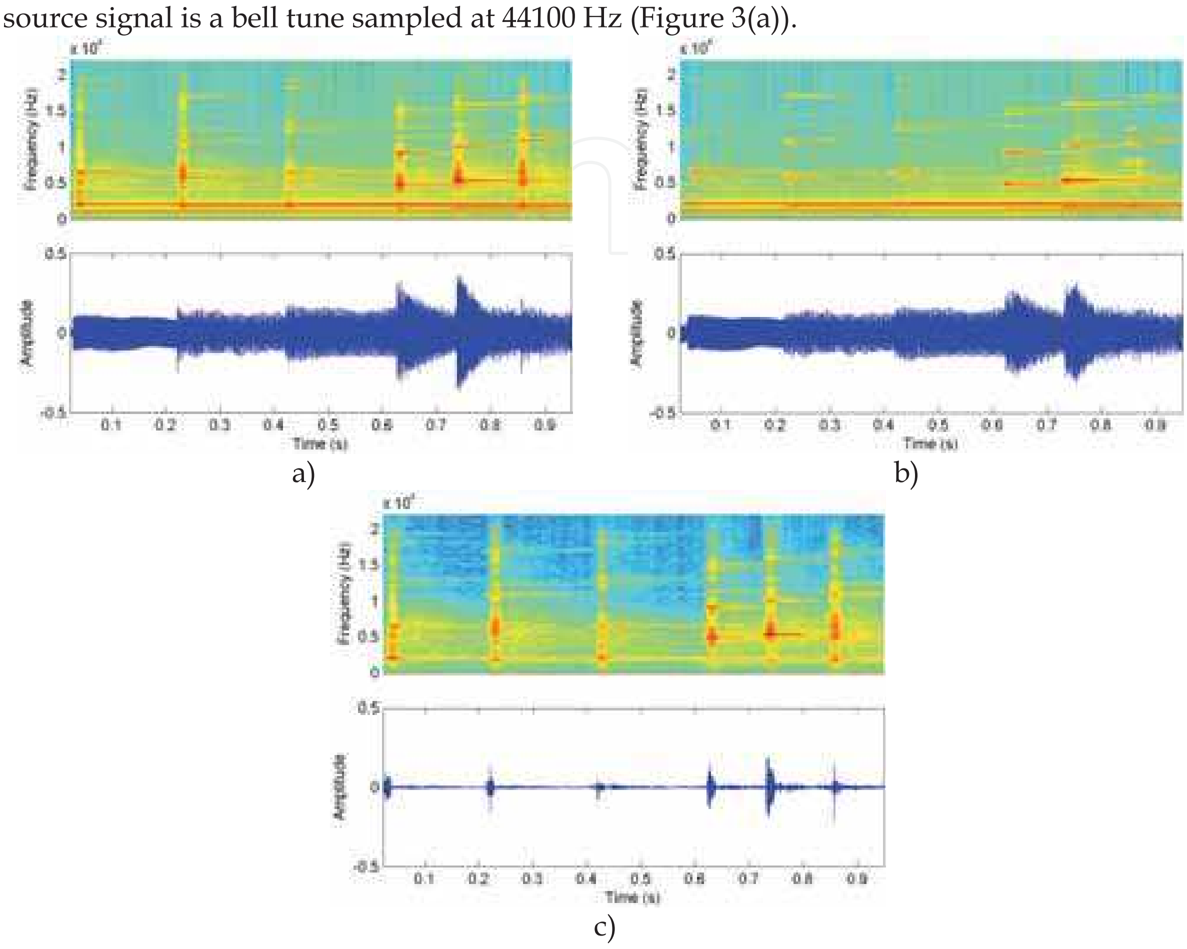


Fig. 3. Periodic/stochastic separation of an audio signal: a) source signal; b) periodic part; c) stochastic part

The analysis was carried out using the following settings: analysis frame length – 48 ms, analysis step – 14 ms, filter bandwidths – 70Hz, windowing function – the Hamming window. The synthesized periodic part is shown in Figure 3(b). As can be seen from the spectrogram, the periodic part contains only long sinusoidal components with high energy localization. The transients are left untouched in the residual signal that is presented in Figure 3(c). The periodic/residual ratio is rather high (14.77 dB) that indicates that the source signal is of a tonal nature.

4.2 Harmonic analysis

As was mentioned above it is possible to use frequency-modulated filters in speech applications in order to make accurate estimation of higher-order harmonics. The analysis process consists of the two following stages:

- fundamental frequency contour estimation and voiced/unvoiced classification;
- harmonic parameters estimation with fundamental frequency adjustment.

The fundamental frequency is estimated first in order to get rough frequency contours of the harmonic components needed for filter synthesis.
The problem of initial fundamental frequency estimation comes to finding a periodical component with the lowest possible frequency and sufficiently high energy at the same time. Within the fundamental frequency range ([60,420] Hz) all periodical components are extracted by means of the described sinusoidal analysis technique and then the suitable one is considered as the fundamental. In order to reduce computational complexity the source signal is filtered by a low-pass filter before the estimation. If it is not possible to track a long continuous sinusoid the corresponding frames are classified as unvoiced.
Having pitch contour estimated it is possible to use frequency-modulated filters that may enhance parameters estimation accuracy for harmonics with significant frequency modulations. Required centre frequency of the filter bands $F_c(n)$ are estimated as the instantaneous fundamental frequency $f_0(n)$ multiplied by the number k of the respective harmonic $F_C^k(n) = kf_0(n)$. The estimation procedure goes from the first harmonic to the last, adjusting fundamental frequency at every step. The fundamental frequency recalculation formula can be written as follows:

$$f_0(n) = \sum_{i=0}^{k} \frac{f_i(n)\mathrm{MAG}_i(n)}{(i+1)\sum_{j=0}^{k}\mathrm{MAG}_j(n)}. \tag{28}$$

The fundamental frequency values become more precise while moving up the frequency range. It allows making proper filter synthesis for increasing harmonic order k. The required harmonic parameters are estimated using expressions (27) and (23)-(25). The stochastic part of the signal is calculated by the formula (4).

5. Linear predictive coding

LPC model assumes that a given signal sample $s(n)$ can be approximated as a linear combination of the p past speech samples that leads to the following equality:

$$s(n) = \sum_{i=1}^{p} a_i\, s(n-i) + Gu(n), \tag{29}$$

where $a_1, a_2, \ldots, a_p$ are prediction coefficients, $u(n)$ is a normalized excitation and G is the gain of the excitation (Rabiner and Juang, 1993). In z-domain the following transfer function can be written:

$$H(z) = \frac{G}{1-\sum_{i=1}^{p} a_i z^{-i}} = \frac{G}{A(z)}. \tag{30}$$

The prediction error $e(n)$ is defined as the difference between the source and predicted samples:

$$e(n) = s(n) - \tilde{s}(n) = s(n) - \sum_{k=1}^{p} a_k s(n-k). \tag{31}$$

The basic problem of LPC is to find the set of predictor coefficients that minimize the mean-square prediction error. There are two primary solutions to this problem: the autocorrelation and covariance methods.

The autocorrelation method assumes that $s(n) = 0$ outside the interval $0 \leq n < N$ and minimizes the prediction error within infinity. It comes to the system of linear equations (Markel and Gray, 1976):

$$\sum_{i=1}^{p} a_i r(|i-j|) = -r(j), \tag{32}$$

where $j = 1,2,\ldots,p$ and $r(l)$ is the autocorrelation function $r(l) = \sum_{n=0}^{N-1-l} s(n)s(n+l),\, l \geq 0$.
The covariance method uses the interval where the signal is defined and can be expressed as the system:

$$\sum_{i=1}^{p} a_i c_{ij} = -c_{0j}, \tag{33}$$

where $j = 1,2,\ldots,p$ and $c_{ij} = \sum_{n=p}^{N-1} s(n-i)s(n-j)$.
The autocorrelation method always produces a stable solution (i.e. all the roots of $A(z)$ are within the unit circle). Unlike it the covariance method does not and therefore it is less popular in speech processing though it may give more accurate results (Markel and Gray, 1976). The frequency domain behaviour of the $A(z)$ can be derived by evaluating

$$H(e^{i\omega}) = \frac{G}{1 - \sum_{k=1}^{p} a_k e^{-j\omega k}} = \frac{G}{A(e^{i\omega})}. \tag{34}$$

6. Conversion of sinusoidal parameters into prediction coefficients

6.1 System derivation

The conversion problem consists in finding the set of linear prediction coefficients $a_1(n),\ldots,a_p(n)$ that provide the closest possible spectral envelope $A(e^{i\omega})$ to the one specified by parameters of the sinusoidal model $\mathrm{MAG}_1(n),\ldots,\mathrm{MAG}_K(n)$ and $f_1(n),\ldots,f_K(n)$.
An obvious solution is to synthesize the periodic signal, specified by the parameters, and then apply a conventional LPC analysis technique in order to estimate the prediction coefficients. Although this approach seems very simple it is not the simplest regarding computation complexity and, moreover, is not the most accurate. If one uses the autocorrelation method it is necessary to analyze a long frame to provide good results. The covariance method theoretically can have better performance however it requires at least one period of the fundamental and is not used for spectral analysis because of specific spectrum interpretation (Markel and Gray, 1976).
Let us consider a sinusoid with a constant amplitude MAG, constant frequency f and zero initial phase:

$$s(n) = \mathrm{MAG}\cdot\cos(fn). \tag{35}$$

The prediction error can be written in the following way:

$$\begin{aligned} e(n) = s(n) - \tilde{s}(n) &= \mathrm{MAG}\cdot\cos(fn) - \sum_{i=1}^{p} \mathrm{MAG}\cdot a_i \cos\big(f(n-i)\big) = \\ &= \mathrm{MAG}\cdot\left[1 - \sum_{i=1}^{p} a_i \cos(fi)\right]\cos(fn) - \mathrm{MAG}\cdot\left[\sum_{i=1}^{p} a_i \sin(fi)\right]\sin(fn). \end{aligned} \tag{36}$$

The prediction error is a sinusoid, which energy can be characterized by the squared amplitude:

$$E_a^2 = \mathrm{MAG}^2 \cdot \left(\left[1 - \sum_{i=1}^{p} a_i \cos(fi) \right]^2 + \left[\sum_{i=1}^{p} a_i \sin(fi) \right]^2 \right). \tag{37}$$

The residual of a harmonic signal is also a harmonic signal. It is possible to evaluate prediction coefficients that minimize the sum of squared amplitudes of the residual. Having an instantaneous vector of sinusoidal amplitudes $\mathrm{MAG}_1(n), \dots, \mathrm{MAG}_K(n)$ and frequencies $f_1(n), \dots, f_K(n)$ the relative residual energy can be evaluated as the following sum:

$$E_a^2 = \sum_{k=1}^{K} \mathrm{MAG}_k(n)^2 \left(\left[1 - \sum_{i=1}^{p} a_i \cos(f_k(n)i) \right]^2 + \left[\sum_{i=1}^{p} a_i \sin(f_k(n)i) \right]^2 \right). \tag{38}$$

In order to minimize E_a^2 it is possible to use the basic minimization approach by finding partial derivatives with respect to variables a_i and then solving the system of linear equations. Eventually the following system can be derived:

$$\sum_{i=1}^{p} a_i q(|i-j|) = -q(j), \tag{39}$$

where $j = 1,2, \dots, p$ and $q(l) = \sum_{k=1}^{K} \mathrm{MAG}_k(n) \cos(f_k(n)l)$, $(l \geq 0)$.

The system is similar to the one in autocorrelation method and can be solved accordingly. There are several well-studied approaches that provide simple and effective solutions (Huang et al., 2001).

Rank of the matrix

$$Q = \begin{bmatrix} q(0) & \cdots & q(p-1) \\ \vdots & \ddots & \vdots \\ q(p-1) & \cdots & q(0) \end{bmatrix} \tag{40}$$

does not exceed $2K$ and therefore there is no need to choose $p > 2K$. However, if the prediction order p is to be more than $2K$ the system should be reduced to $2K$ order and then $p - 2K$ zeros should be added to the evaluated prediction coefficients.

In order to show how proposed conversion technique compares with other methods the spectrum analysis of a sinusoidal signal is illustrated in Figure 4. The signal consists of two sinusoids with equal constant amplitudes $\mathrm{MAG}_1(n) = 1$, $\mathrm{MAG}_2(n) = 1$ and harmonically related frequencies $f_1(n) = 200Hz$, $f_2(n) = 400Hz$. The sampling frequency is 8kHz. The results were obtained by different approaches with the same prediction order $p = 8$. In order to provide accurate results 400 samples of the signal weighted by the Hamming window were used for the autocorrelation method and one exact period of the f_1 (i.e. 40 samples) was used for the covariance method. The obtained prediction coefficients are listed in Table 1.

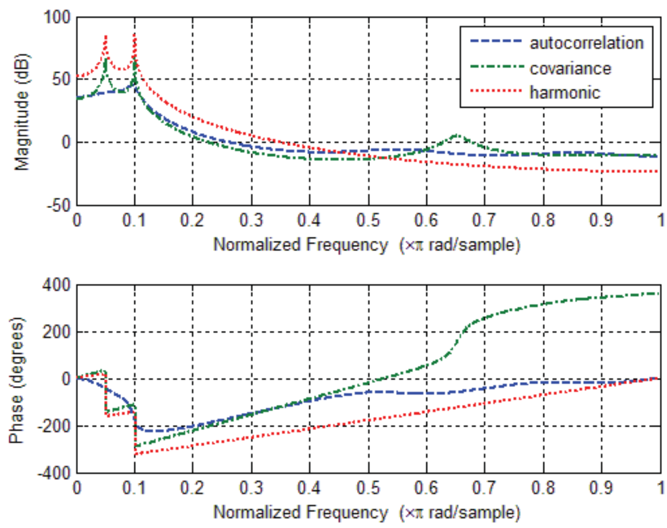


Fig. 4. LPC spectrum envelopes obtained through different methods

autocorrelation	covariance	harmonic
prediction coefficients		
-1.9816	-1.7037	-3.8775
0.6289	0	5.7574
0.4239	0	-3.8775
0.2187	1.7242	1.0000
0.0145	0	0
-0.1881	-1.4448	0
-0.3884	0	0
0.2889	0.4437	0
residual, dB		
-40.36	-278.99	-246.79

Table 1. LPC analysis result

As can be seen from the presented example the covariance method gives the smallest residual, however the conversion technique gives the most adequate spectral envelope. The autocorrelation method produces heavily smoothed spectrum and requires lengthening of the analysis frame in order to give more accurate results.

6.2 Stability problem

Almost all signal processing applications that use LPC require stability of the filter $1/A(z)$. The stability is guaranteed if all the roots of the polynomial $A(z)$ are inside the unit circle. The proposed technique may produce an unstable filter (when $p \geq 2K$) with roots on the circle. In this section a method of modifying prediction coefficients is proposed that provides a stable filter in such cases.

The method is based on the autocorrelation approach. Let us consider a signal $s(n) = t(n)$, $1 \leq n \leq 2p$, that satisfy the following conditions $\sum_{n=1}^{p} |t(n)| > 0$ and $\sum_{n=p+1}^{2p} |t(n)| = 0$.

Stability of the filter can be guaranteed if the coefficients minimize the prediction error for both $t(n)$ and (38).
Using (33) residual minimization of the signal $t(n)$ leads to the following system:

$$\sum_{i=1}^{p} a_i c_{ij} = 0 \tag{41}$$

where $j = 1,2, \dots, p$ and $c_{ij} = \sum_{n=p}^{N-1} s(n-i)s(n-j)$.
The following combination of (39) and (41) gives the required system:

$$\sum_{i=1}^{p} a_i\left[c_{ij} + q(|i-j|)\right] = -q(j). \tag{42}$$

Although choosing $t(n)$ may be arbitrary, it is possible to find a sequence that changes only one element $q(0)$ of the system (39). Let us consider $t(n)$ specified in the following way:

$$t(n) = \begin{cases} 0, & n \neq p \\ \Delta d, & n = p \end{cases}. \tag{43}$$

In this case the c_{ij} in (41) becomes

$$c_{ij} = \begin{cases} 0, & i \neq j \\ \Delta d, & i = j \end{cases}, \tag{44}$$

and (42) can be written in the following form:

$$\sum_{i=1}^{p} a_i q(|i-j|) = -q(j) \tag{45}$$

where $j = 1,2, \dots, p$ and $q(l) = \begin{cases} \sum_{k=1}^{K} \mathrm{MAG}_k(n)\cos(f_k(n)l) + \Delta d\,, & l = 0 \\ \sum_{k=1}^{K} \mathrm{MAG}_k(n)\cos(f_k(n)l), & l > 0 \end{cases}.$

The value of Δd specifies how close the roots $A(z)$ are to the unit circle. The closer Δd is to zero the closer filter is to instability. However large values of the parameter may degrade prediction accuracy.
Figure 5 shows a spectral analysis of a harmonic signal using different values of Δd. Increasing stabilizing parameter Δd makes the conversion envelope smoother and some large values can even make it very close to the autocorrelation one.

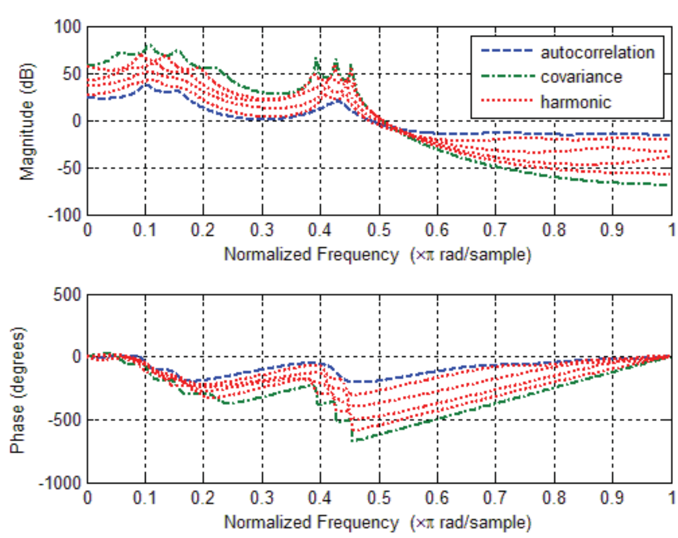


Fig. 5. LPC spectrum analysis of the harmonic signal with $\Delta d = 10^{-5}, 10^{-4}, 10^{-3}, 10^{-2}$

6.3 Instantaneous LPC analysis

In the present subsection the proposed conversion technique is applied to a synthetic frequency-modulated harmonic signal.

The signal frame consists of two harmonic components with frequency modulations (Figure 6). The frame length is 512 samples. The harmonic components have constant amplitudes (Figure 6(b)) and rapidly increasing frequencies (Figure 6(c)). The prediction coefficients for the frame were obtain via autocorrelation and harmonic conversion techniques (Figure 6 and Figure 7 respectively, prediction order is 14 in both cases).

The autocorrelation produces only one set of prediction coefficients for the entire frame (like in real speech/audio coding systems). The frame was weighted by the Hamming window before estimation. The obtained spectrum envelopes and residuals are presented in Figure 7(a)-(b). The spectrum reflects average values of instantaneous amplitudes and frequencies of the harmonic components. The energy of the residual signal is lower close to the centre of the frame; the total energy of the residual is -29.66 dB.

The analysis results obtained by direct sinusoidal parameters conversion are shown in Figure 7(c)-(d). The prediction coefficients were recalculated for every sample of the frame. The spectrum picture reflects instantaneous behaviour of the harmonic components. The energy of the residual signal is higher close to the centre of the frame with the total energy of -61.18 dB. Thus one can say that the energy of the source frequency-modulated signal was much more accurately localized both in time and frequency domain.

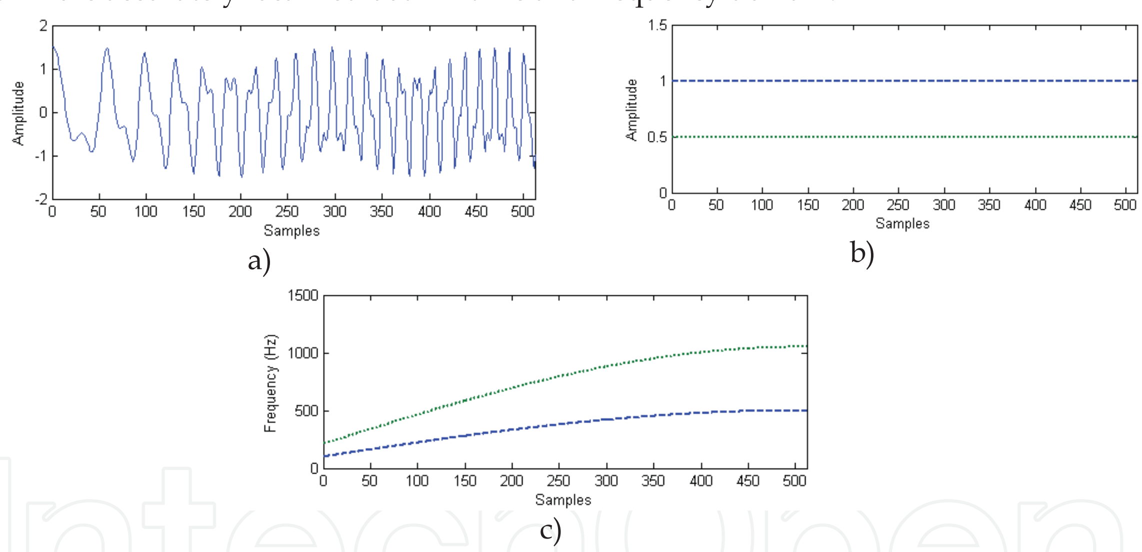
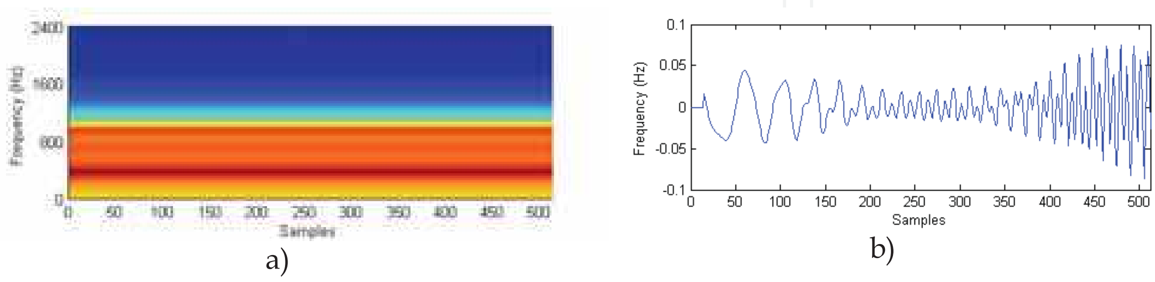
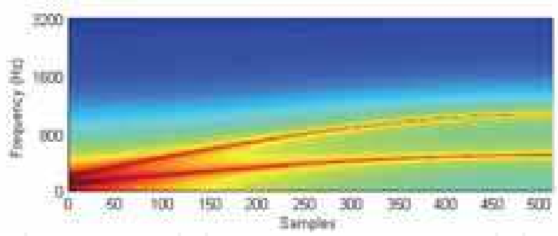


Fig. 6. Harmonic signal with frequency modulations: a) waveform; b) amplitudes of the harmonic components; c) frequencies of the harmonic components





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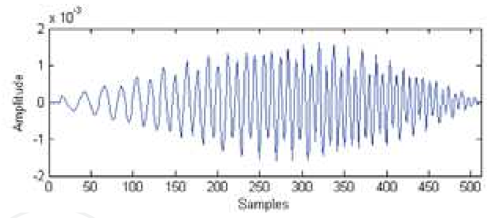


d)

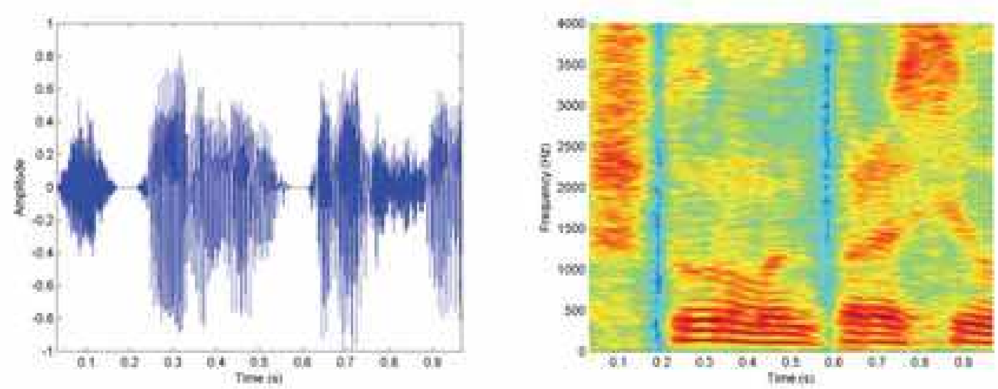
Fig. 7. Frame analysis by autocorrelation and sinusoidal parameters conversion: a) autocorrelation spectrum estimation; b) autocorrelation residual; c) instantaneous LPC spectrum; d) instantaneous residual

7. Experimental applications

The described methods of sinusoidal and harmonic analysis can be used in several speech processing systems. This section presents some application results.

7.1 Application of harmonic analysis to parametric speech coding

Accurate estimation of sinusoidal parameters can significantly improve performance of coding systems. Well-known compressing algorithms that use sinusoidal representation may benefit from fine accurate harmonic/residual separation, providing higher quality of the decoded signal. The described analysis technique has been applied to hybrid speech and audio coding (Petrovsky et al., 2008).



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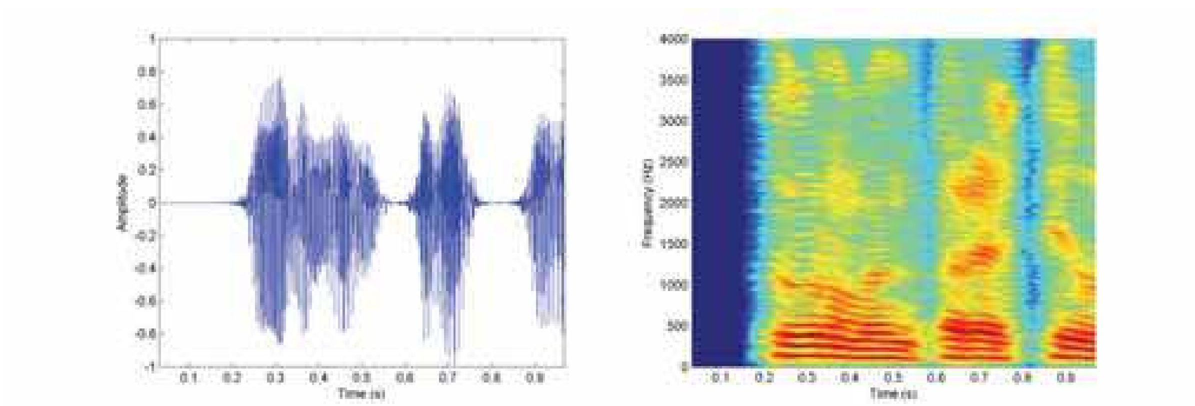

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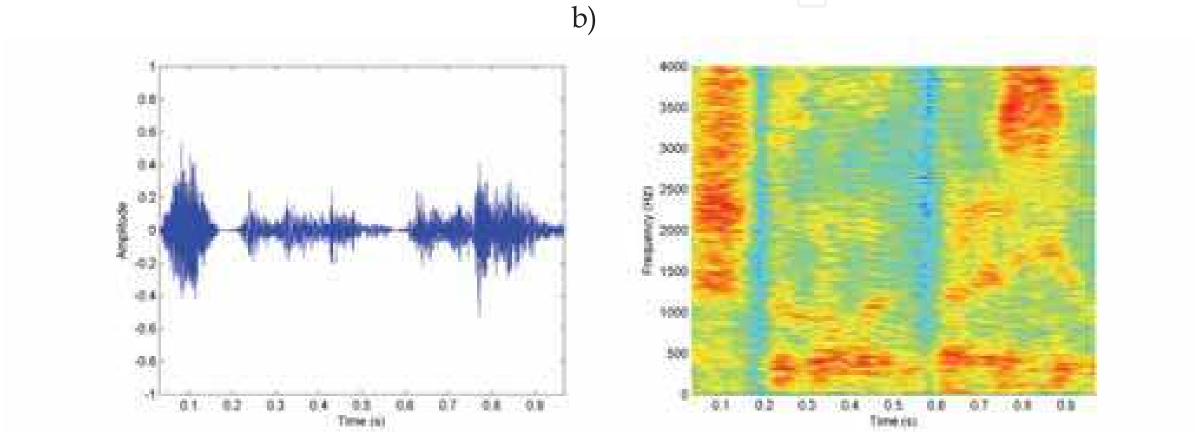


c)

Fig. 8. Harmonic parameters estimation: a) source signal; b) estimated deterministic part; c) estimated stochastic part

An example of harmonic analysis is presented in Figure 8(a). The source signal is a phrase uttered by a male speaker (F_s = 8kHz). The deterministic part of the signal Figure 8(b) was synthesized using estimated harmonic parameters and subtracted from the source in order to get the stochastic part Figure 9(c). The spectrograms show that all steady harmonics of the source are modelled by sinusoidal representation when the residual part contains transient and noise components.

7.2 Harmonic analysis in TTS systems

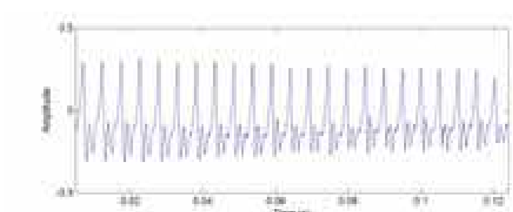
This subsection presents an experimental application of sinusoidal modelling with proposed analysis techniques to a TTS system. Despite the fact that many different techniques have been proposed, segment concatenation is still the major approach to speech synthesis. The speech segments (allophones) are assembled into synthetic speech and this process involves time-scale and pitch-scale modifications in order to produce natural-like sounds. The concatenation can be carried out either in time or frequency domain. Most time domain techniques are similar to the Pitch-Synchronous Overlap and Add method (PSOLA) (Moulines and Charpentier, 1990). The speech waveform is separated into short-time signals by the analysis pitch-marks (that are defined by the source pitch contour) and then processed and joined by the synthesis pitch-marks (that are defined by the target pitch contour). The process requires accurate pitch estimation of the source waveform. Placing analysis pitch-marks is an important stage that significantly affects synthesis quality. Frequency domain (parametric) techniques deal with frequency representations of the segments instead of their waveforms what requires prior transformation of the acoustic database to frequency domain. Harmonic modelling can be especially useful in TTS systems for the following reasons:

- explicit control over pitch, tempo and timbre of the speech segments that insures proper prosody matching ;
- high-quality segment concatenation can be performed using simple linear smoothing laws;
- acoustic database can be highly compressed;
- synthesis can be implemented with low computational complexity.

In order to perform real-time synthesis in harmonic domain all waveform speech segments should be analysed and stored in new database, which contains estimated harmonic parameters and waveforms of stochastic signals. The analysis technique described in the chapter can be used for parameterization. In Figure 9 a result of such parameterization is presented. The analysed segment is sound [a:] of a female voice.

Speech concatenation with prosody matching can be efficiently implemented using sinusoidal modelling. In order to modify durations of the segments the harmonic parameters are recalculated at new instants, that are defined by some dynamic warping function, the noise part is parameterized by spectral envelopes and then time-scaled as described in (Levine and Smith, 1998).

Changing the pitch of a segment requires recalculation of harmonic amplitudes, maintaining the original spectral envelope. Noise part of the segment is not affected by pitch shifting and obviously should remain untouched. Let us consider the instantaneous frequency envelope as a function $E(n,f)$ of two parameters (sample number and frequency respectively). After harmonic parameterization the function is defined at frequencies of the harmonic components that were calculated at the respective instants of time: $E\left(n, f_k(n)\right) = \mathrm{MAG}_k(n)$. In order to get the completely defined function the piecewise-linear interpolation is used. Such interpolation has low computational complexity and, at the same time, gives sufficiently good approximation (Dutoit 1997).



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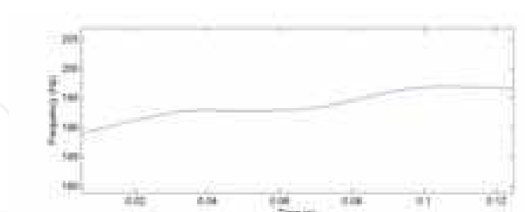

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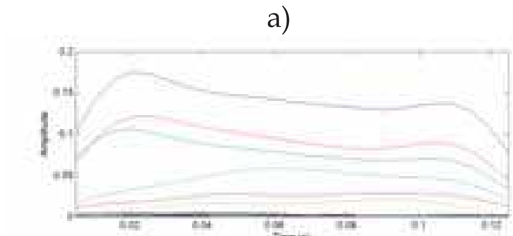

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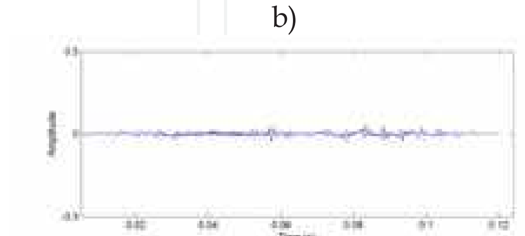

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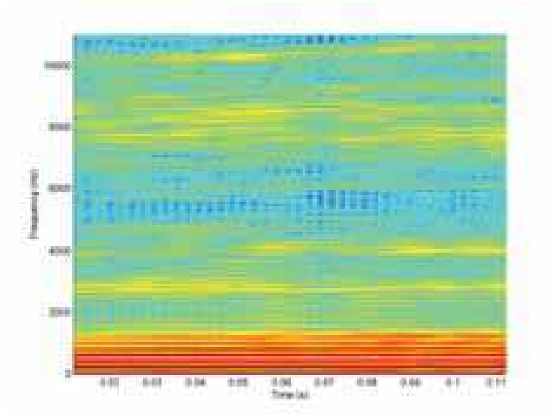
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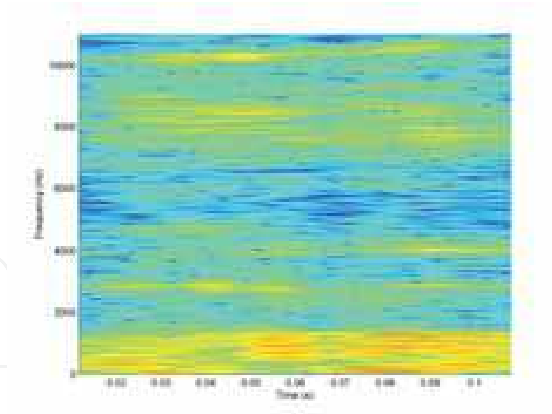

f)

Fig. 9. Segment analysis: a) source waveform segment; b) estimated fundamental frequency contour; c) estimated harmonic amplitudes; d) estimated stochastic part; e) spectrogram of the source segment; f) spectrogram of the stochastic part

The periodical signal $\bar{s}(n)$ with pitch shifting can be synthesized from its parametric representation as follows:

$$\bar{s}(n) = \sum_{k=1}^{K} E\left(n, \bar{f}_k(n)\right) \cos\bar{\varphi}_k(n). \quad (46)$$

Phases of harmonic components $\bar{\varphi}_k(n)$ are calculated according to the new fundamental frequency contour $\bar{f}_0(n)$:

$$\bar{\varphi}_k(n) = \sum_{i=0}^{n} \frac{2\pi\bar{f}_k(i)}{F_s} + \bar{\varphi}_k^{\Delta}(n). \quad (47)$$

Harmonic frequencies are calculated by the formula (3):

$$\bar{f}_k(n) = k\bar{f}_0(n). \quad (48)$$

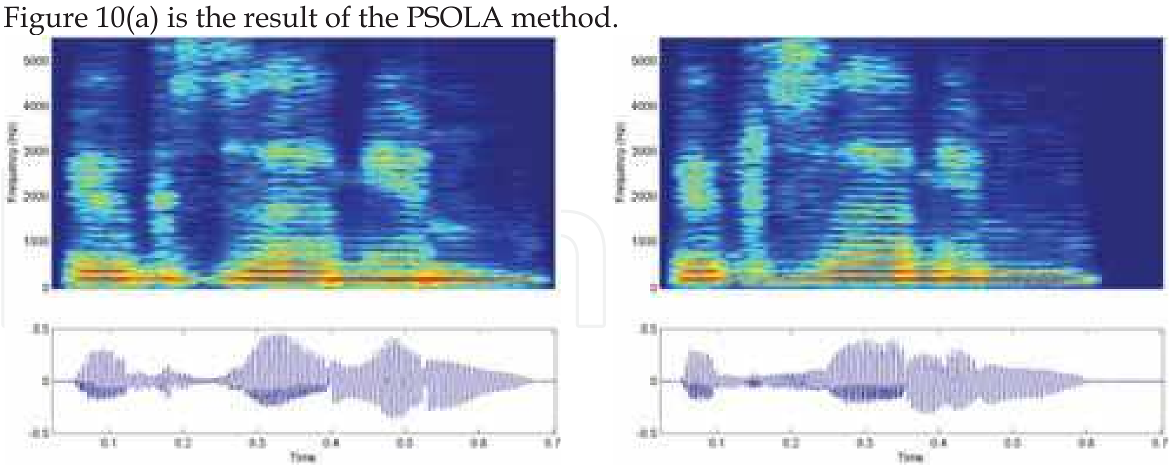
Additional phase difference $\bar{\varphi}_k^{\Delta}(n)$ is used in order to maintain relative phases of harmonics and the fundamental:

$$\bar{\varphi}_k^{\Delta}(n) = \varphi_k(n) - (k+1)\varphi_0(n). \quad (49)$$

In synthesis process the phase differences $\bar{\varphi}_k^{\Delta}(n)$ are good substitutions of phase parameters $\varphi_k(n)$ since all the harmonics are kept coordinated regardless of the frequency contour and the initial phase of the fundamental.

Due to parametric representation spectral amplitude and phase mismatches at segments borders can be efficiently smoothed. Spectral amplitudes of acoustically related sounds can be matched by simultaneous fading out and in that is equivalent to linear spectral smoothing (Dutoit 1997). Phase discontinuities are also can be matched by linear laws taking into account that harmonic components are represented by their relative phases $\bar{\varphi}_k^{\Delta}(n)$. However, large discontinuities (when absolute difference exceeds π) should be eliminated by adding multiplies of $\pm 2\pi$ to the phase parameters of the next segment. Thus, phase parameters are smoothed in the same way as spectral amplitudes, providing imperceptible concatenation of the segments.

In Figure 10 the proposed approach is compared with PSOLA synthesis, implemented as described in (Moulines and Charpentier, 1990). A fragment of speech in Russian was synthesized through two different techniques using the same source acoustic database. The database segments were picked out from the speech of a female speaker. The sound sample in Figure 10(a) is the result of the PSOLA method.



a) b)

Fig. 10. TTS synthesis comparison: a) PSOLA synthesis; b) harmonic domain concatenation

In Figure 10(b) the sound sample is shown, that is the result of the described analysis/synthesis approach. In order to get the parametric representation of the acoustic database each segment was classified either as voiced or unvoiced. The unvoiced segments were left untouched while the voiced were analyzed by the technique described in Section 4, then prosody modifications and segment concatenation were carried out. Both sound samples were synthesized at 22kHz, using the same predefined pitch contour.

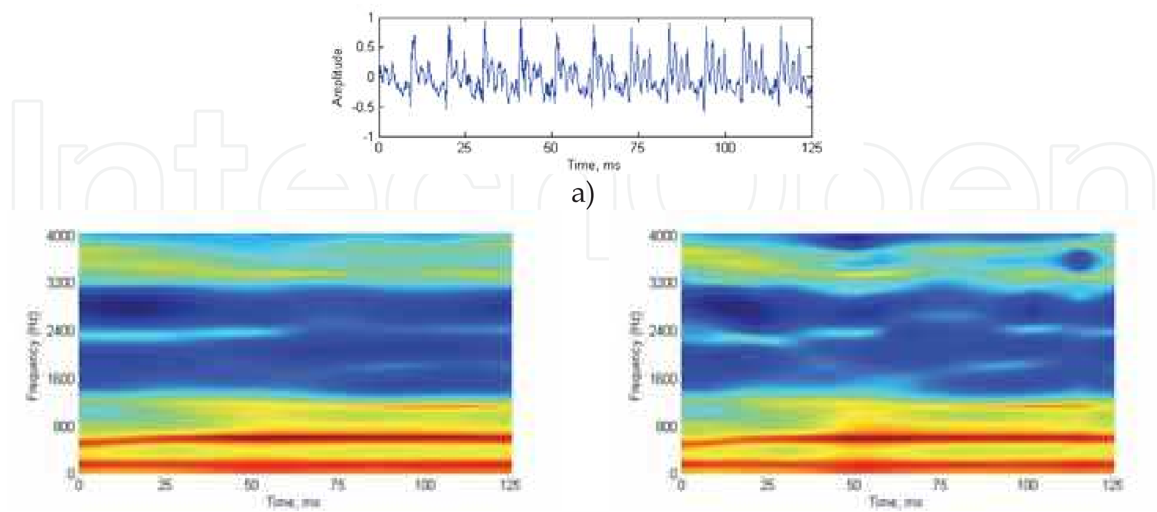
As can be noticed from the presented samples the time domain concatenation approach produces audible artefacts at segment borders. They are caused by phase and pitch mismatching, that cannot be effectively avoided during synthesis. The described parametric approach provides almost inaudible phase and pitch smoothing, without distorting spectral and formant structure of the segments. The experiments have shown that this technique is good enough even for short and fricative segments, however, the short Russian ‘r’ required special adjustment of the filter parameters at the analysis stage in order to make proper analysis of the segment.

The main drawback of the described approach is noise amplification immediately at segment borders where the analysis filter gives less accurate results because of spectral leakage. In the current experiment the problem was solved by fading out the estimated noise part at segment borders. It is also possible to pick out longer segments at the database preparation stage and then shorten them after parameterization.

7.3 Instantaneous LPC analysis of speech

LPC-based techniques are widely used for formant tracking in speech applications. Making harmonic analysis first and then performing parameters conversion a higher accuracy of formant frequencies estimation can be achieved. In Figure 11 a result of voiced speech analysis is presented. The analysed signal (Figure 11(a)) is a vowel [a:] uttered by a male speaker. This sound was sampled at 8kHz and analyzed by the autocorrelation (Figure 11(b)) and the harmonic conversion (Figure 11(c)) techniques. In order to give expressive pictures prediction coefficients were updated for every sample of the signal in both cases.

The autocorrelation analysis was carried out with analysis frame 512 samples in length, weighted by the Hamming window. Prediction order was 20 in both cases.



b) c)

Fig. 11. Instantaneous formant analysis: a) source signal; b) autocorrelation analysis; c) instantaneous LPC analysis

As can be seen from the pictures harmonic analysis with subsequent conversion into prediction coefficients gives more localized formant trajectories. Some of them have more complex form, however overall formant structure of the signal remains the same.

8. Conclusions

An estimation technique of instantaneous sinusoidal parameters has been presented in the chapter. The technique is based on narrow-band filtering and can be applied to audio and speech sounds. Signals with harmonic structure (such as voiced speech) can be analysed using frequency-modulated filters with adjustable impulse response. The technique has a good performance considering that accurate estimation is possible even in case of rapid frequency modulations of pitch. A method of pitch detection and estimation has been described as well. The use of filters with modulated impulse response, however, requires precise estimation of instantaneous pitch that can be achieved through pitch values recalculation during the analysis process. The main disadvantage of the method is high computational cost in comparison with STFT.

Some experimental applications of the proposed approach have been illustrated. The sinusoidal modelling based on the presented technique has been applied to speech coding, and TTS synthesis with wholly satisfactory results.

The sinusoidal model can be used for estimation of LPC parameters that describe instantaneous behaviour of the periodical signal. The presented conversion technique of sinusoidal parameters into prediction coefficients provides high energy localization and smaller residual for frequency-modulated signals, however overall performance entirely depends on the quality of prior sinusoidal analysis. The instantaneous prediction

coefficients allow implementing fine formant tracking that can be useful in such applications as speaker identification and speech recognition.
Future work is aimed at further investigation of the analysis filters and their behaviour, finding optimized solutions for evaluation of sinusoidal parameters. It might be some potential in adapting described methods to other applications such as vibration analyzer of mechanical devices and diagnostics of throat diseases.

9. Acknowledgments

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10. References

Abe, T.; Kobayashi, T. & Imai, S. (1995). Harmonics tracking and pitch extraction based on instantaneous frequency, *Proceedings of ICASSP 1995.* pp. 756–759. 1995.

Azarov, E.; Petrovsky, A. & Parfieniuk, M. (2008). Estimation of the instantaneous harmonic parameters of speech, *Proceedings of the 16th European Signal Process. Conf. (EUSIPCO-2008)*, CD-ROM, Lausanne, 2008.

Boashash, B. (1992). Estimating and interpreting the instantaneous frequency of a signal, *Proceedings of the IEEE*, Vol. 80, No. 4, (1992) 520-568.

Dutoit, T. (1997). *An Introduction to Text-to-speech Synthesis*, Kluwer Academic Publishers, the Netherlands.

Gabor, D. (1946). Theory of communication, *Proc. IEE*, Vol.93, No. 3, (1946) 429-457.

Gianfelici, F.; Biagetti, G.; Crippa, P. & Turchetti, C. (2007) Multicomponent AM–FM Representations: An Asymptotically Exact Approach, *IEEE Transactions on Audio, Speech, and Language Processing*, Vol. 15, No. 3, (March 2007) 823-837.

Griffin, D. & Lim, J. (1988). Multiband excitation vocoder, *IEEE Trans. On Acoustics, Speech and Signal Processing*, Vol. 36, No. 8, (1988) 1223-1235.

Hahn, S. L. (1996) *Hilbert Transforms in Signal Processing*, MA: Artech House, Boston.

Huang, X; Acero, A. & Hon H.W. (2001). *Spoken language processing,* Prentice Hall, New Jersey.

Levine, S. & Smith, J. (1998). A Sines+Transients+Noise Audio Representation for Data Compression and Time/Pitch Scale Modifications, *AES 105th Convention*, Preprint 4781, San Francisco, CA, USA.

Maragos, P.; Kaiser, J. F. & Quatieri, T. F. (1993). Energy Separation in Signal Modulations with Application to Speech Analysis”, *IEEE Trans. On Signal Process.*, Vol. 41, No. 10, (1993) 3024-3051.

Markel J.D. & Gray A.H. (1976) *Linear prediction of speech,* Springer-Verlag Berlin Heidelberg, New York.

McAulay, R. J. & Quatieri, T. F. (1986). Speech analysis/synthesis based on a sinusoidal representation. *IEEE Trans. On Acoustics, Speech and Signal Process.,* Vol. 34, No. 4, (1986) 744-754.

McAulay, R. J. & Quateri T. F. (1992). The sinusoidal transform coder at 2400 b/s, *Proceedings of Military Communications Conference,* Calif, USA, October 1992, San Diego.

Moulines, E. & Charpentier, F. (1990). Pitch Synchronous Waveform Processing Techniques for Text-to-Speech Synthesis Using Diphones. *Speech Communication*, Vol.9, No. 5-6, (1990) 453-467.

Painter, T. & Spanias, A. (2003). Sinusoidal Analysis-Synthesis of Audio Using Perceptual Criteria. *EURASIP Journal on Applied Signal Processing,* No. l, (2003) 15-20.

Petrovsky, A.; Stankevich, A. & Balunowski, J. (1999). The order tracking front-end algorithms in the rotating machine monitoring systems based on the new digital low order tracking, *Proc. of the 6th Intern. Congress "On sound and vibration"*, pp.2985-2992, Denmark, 1999, Copenhagen.

Petrovsky, A.; Azarov, E. & Petrovsky, A. (2008). Harmonic representation and auditory model-based parametric matching and its application in speech/audio analysis, *AES 126th Convention*, Preprint 7705, Munich, Germany.

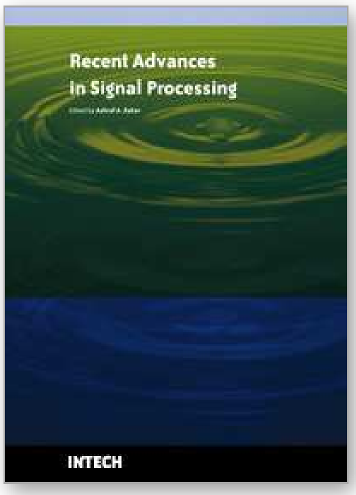
Rabiner, L. & Juang, B.H. (1993). *Fundamentals of speech recognition,* Prentice Hall, New Jersey.

Serra, X. (1989). A system for sound analysis/transformation/synthesis based on a deterministic plus stochastic decomposition, *Ph.D. thesis*, Stanford University, Stanford, Calif, USA.

Spanias, A.S. (1994). Speech coding: a tutorial review. *Proc. of the IEEE,* Vol. 82, No. 10, (1994) 1541-1582.

Weruaga, L. & Kepesi, M. (2007). The fan-chirp transform for non-stationary harmonic signals, *Signal Processing*, Vol. 87, issue 6, (June 2007) 1-18.

Zhang, F.; Bi, G. & Chen Y.Q. (2004). Harmonic transform, *IEEE Proc.-Vis. Image Signal Process.*, Vol. 151, No. 4, (August 2004) 257-264.



Recent Advances in Signal Processing
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The signal processing task is a very critical issue in the majority of new technological inventions and challenges in a variety of applications in both science and engineering fields. Classical signal processing techniques have largely worked with mathematical models that are linear, local, stationary, and Gaussian. They have always favored closed-form tractability over real-world accuracy. These constraints were imposed by the lack of powerful computing tools. During the last few decades, signal processing theories, developments, and applications have matured rapidly and now include tools from many areas of mathematics, computer science, physics, and engineering. This book is targeted primarily toward both students and researchers who want to be exposed to a wide variety of signal processing techniques and algorithms. It includes 27 chapters that can be categorized into five different areas depending on the application at hand. These five categories are ordered to address image processing, speech processing, communication systems, time-series analysis, and educational packages respectively. The book has the advantage of providing a collection of applications that are completely independent and self-contained; thus, the interested reader can choose any chapter and skip to another without losing continuity.

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