A Hybrid Computing Adaptive Filtering Methods for Parameter Estimation of Nonstationary Power Signals

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Summary
This paper presents a new approach in the detection, localization, and classification of frequency and amplitude changes in nonstationary signal waveforms using a variable window short-time Fourier Transform (STFT) known as ST in short and an Extended Complex Kalman Filter (CEKF). Unlike the fixed window STFT, the variable window Short-time Fourier Transform has excellent time-frequency resolution characteristics and provides detection, localization, and visual patterns suitable for automatic recognition of time-varying signal patterns. The CEKF, on the other hand, provides automatic classification and measurements of the frequent amplitude, and phase of sinusoids embedded in noise. The technique is applied to both simulated and experimentally obtained waveform disturbances in the presence of additive noise and the results reveal significant accuracy in completely localizing the changes in amplitude, frequency, and phase of nonstationary sinusoids in noise.

Key words:
S-Transform (ST), Kalman Filter, Time-frequency localization, Frequency estimation, Noise rejection and time varying amplitude and phase estimation.

1. Introduction

In this paper, we propose a novel digital signal processing technique for the detection, classification and measurement of the parameters of a sinusoidal signal with time varying amplitude, phase, and frequency which are usually contaminated with noise.
The new developments in the area of signal processing [1], [12] provides high performance signal analysis because they employ understandable signal representations than just time or frequency representation of signals. These potential tools have been successfully applied in geophysics, acoustics, image processing, data compression and recently power quality analysis [2 - 5]. Several techniques, leading to time-frequency representation and applicable to SDD, are investigated here.
To analyze distorted signal, short time discrete Fourier transform (STFT) is most often used. This transform performs satisfactorily for stationary signals where properties of signals do not change with time. For nonstationary signals, the STFT does not track the signal dynamics properly. On the other hand, the wavelet analysis provides a unified framework for processing distorted signals.
Wavelet analysis [6] is based on the decomposition of a signal according to time-scale, rather than frequency, using basis functions with adaptable scaling properties, which is known as multi resolution analysis. A Wavelet Transform (WT) expands a signal not in terms of a trigonometric polynomial but by wavelets, generated using transition (shift in time) and dilation (compression in time) of a fixed wavelet function. The wavelet function is localized both in time and frequency yielding wavelet coefficients at different scales. This gives the WT much greater compact support for analysis of signals with localized transient components. Several types of wavelets have been considered [7,8,9] for detection, localization, and classification of waveform distortions as both time and frequency information are available by multi resolution analysis. At first the extraction of the occurred disturbance requires its time duration estimation. This information is vital as there is a need to obtain the sampling frequency and the frequency sub-band containing most of the spectral energy. However, this process is very much influenced by the noise superimposed on the signal and the iterative nature of the wavelet transform based algorithms requiring different sampling frequencies for different frequency sub-bands.

The variable window STFT, which is known as S-Transform (ST in short) [10], on the other hand, is an extension to the ideas of WT, and is based on a moving and scalable localizing Gaussian window and has characteristics superior to either of the transforms. The ST is fully convertible from the time domain to 2-D frequency translation domain and then to familiar Fourier frequency domain. The amplitude frequency – time spectrum and the phase – frequency – time spectrum are both useful in defining local spectral characteristics. The superior properties of the ST are due to the fact that the modulating sinusoids are fixed with respect to the time axis while the localizing scalable Gaussian window dilates and translates. As a result, the phase spectrum is absolute in the sense that it always refers to the origin of the time axis. The real and imaginary spectrum can be localized independently with a resolution in time corresponding to the basis function in

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question and the changes in the absolute phase of a constituent frequency can be followed along the time axis. The phase information associated with the ST makes it as an ideal candidate for the detection and classification of distorted signals.

Amongst the several numerical techniques, Kalman filtering [11,12] approaches have attracted widespread attention, as they accurately estimate the amplitude, phase and frequency of a signal buried with noise and harmonics. In this paper, a variation of nonlinear Kalman filter [13] is presented which simplifies the modeling requirement for amplitude and frequency estimation of a signal.

The ST matrix of time varying nonstationary signal samples is computed, and is used to detect and localize and recognize amplitude, frequency, phase change patterns. After a change in any parameter of the signal occurs, the signal samples up to the next change are fed to an Extended Complex Kalman filter to estimate the amplitude, frequency, phase, and harmonic contents of the signal to provide automatic recognition and measurement of the changed parameters. Extensive computer simulation tests are performed to validate the efficacy of the proposed approach.

2. Variable Window STFT (S-Transform)

The short-time Fourier transform of a signal $x(t)$ is given by

$$\mathrm{STFT}(t,f)=\int_{-\infty}^{\infty} x(\tau)w(t-\tau)e^{-2\pi i f\tau}d\tau \quad (1)$$

Where τ and f denote the time and frequency (τ) is the main signal and the position of the translating window is determined by τ, which has the same value as t. An alternate expression for (1) is obtained through the use of convolution theorem as

$$\mathrm{STFT}(t,f)=\int_{-\infty}^{\infty} X(\alpha+f)W(\alpha)e^{-2\pi\alpha t}d\alpha \quad (2)$$

Where W is the Fourier transform of w, and the convolution variable α has the same dimension as f. One of the disadvantages of STFT is the fixed width and height of the window. This causes misinterpretation of signal components with periods longer than the window width and the width that works well with low frequency components can not detect the high frequency components. The S-transform is a time localized Fourier transform and has a window whose width and height vary with frequency. Although the theory of S-Transform has been presented in references [9], [10] and originally by Stockwell etal. [8], some of the equations and computational steps are outlined below:

The general window function *w(t, f)* is chosen as

$$w(t,f)=\frac{1}{\sigma(f)\sqrt{2\pi}}e^{-\frac{t}{2\sigma(f)^2}} \quad (3)$$

Here $\sigma(f)$ is a function of frequency as

$$\sigma(f)=\frac{\beta}{|f|} \quad (4)$$

The window is normalized as

$$\int_{-\infty}^{\infty} w_n(t,f)dt=1 \quad (5)$$

Here β is normally set to a value 0.2 for best overall performance of S-Transform where the contours exhibit the least edge effects and for computing the highest frequency component of very short duration oscillatory transients β is made equal to 5. The S-Transform performs multi resolution analysis on the signal, because the width of its window varies inversely with frequency. This gives high time resolution at high frequencies and on the other hand, high frequency resolution at low frequencies.

The expression for S-transform is given by

$$S(t,f)=\int_{-\infty}^{\infty} x(\tau)\frac{|f|}{\sqrt{2\pi}}-e^{\frac{f^2(t-\tau)^2}{2}}.e^{-2\pi i f\tau}d\tau \quad (6)$$

Here the window function is used as given in (3).

An alternative formulation for S-transform is given by

$$S(t,f)=\int_{-\infty}^{\infty} X(\alpha+f)e^{-\frac{2\pi^2\beta^2\alpha^2}{f^2}}e^{2\pi\alpha t}d\alpha \quad (7)$$

The discrete version of the S-Transform of a signal is obtained as

$$S[j,n]=\sum_{m=0}^{N-1} X[m+n]W[m,n]e^{i\frac{2\pi mj}{N}} \quad (8)$$

Where X[m + n] is obtained by shifting the discrete Fourier Transform (DFT) of x(k) by n, X[m] being given

$$X[m]=\frac{1}{N}\sum_{k=0}^{N-1} x[k]e^{-j\frac{2\pi mk}{N}} \quad (9)$$

and $$W[m+n]=e^{\frac{-2\pi m^2\beta^2}{n}} \quad (10)$$

j, m and n = 0, 1, ….., N-1

Another version of the discrete S-Transform used for computation

$$S[m,n] = e^{-j\frac{2\pi nm}{N}} \sum_{k=-\frac{N}{2}}^{\frac{N}{2}-1} x[m+k] w^*(k,n) e^{i\frac{2\pi nk}{N}} \quad (11)$$

for m = 1, 2, …, M and n = 0, 1, 2, …N/2
where M is the number of data points of the signal x[m], N is the width of the window, the signal vector x[m] is padded at the beginning or at the end with 0.

3. Implementation of S-Transform (ST):

The computation of the S-Transform is efficiently implemented using the convolution theorem and FFT. The following steps are used for the computation of S-Transform:

(i) Compute the DFT of the signal x(k) using FFT software routine and shift spectrum X[m] to X[m+n].
(ii) Compute the gaussian window function $\exp(-2\pi^2\beta^2 m^2 / n^2)$ for the required frequency n.
(iii) Compute the inverse Fourier Transform of the product of DFT and gaussian window function to give the ST matrix.

The output of the S-transform is an n×m matrix, whose rows pertain to frequency and columns indicate time. Each column thus represents the “local spectrum” for that point in time. From the ST matrix we obtain the frequency-time contours having the same amplitude spectrum and these contours can be used to visually classify the nature of the signal and its change of frequency. However, for automatic classification of the signal, the standard deviation (SD) of the most significant contour having the largest frequency amplitude versus time is calculated. Thus SD = std (contour c1) and it can be considered as a measure of the energy of the signal with zero mean. The standard deviation of the nonstationary signal is found to indicate whether the signal belongs to normal class or the disturbed one. Further it can be used to distinguish between amplitude changes or frequency changes. Once the signal is found to contain a frequency, amplitude or phase change, the next step is to compute its duration and magnitude and use the CEKF (Complex Extended Kalman Filter) for the estimation of amplitude, frequency, phase, and the harmonic content if any during the distortion. The next section describes a Complex Extended Kalman Filter for the computation of the above quantities which can be used for further classification of the nature of the disturbance in the signal.

4. Complex Extended Kalman Filter

Measurement and classification of patterns are the important aspects for time varying analysis, and signal STFT whereas ST or Wavelet transform can only localize and classify the distorted signals. Several methods are already developed for the measurement of percentage change in amplitude, frequency, and the harmonic content of the distorted signal. Out of all the approaches Kalman filtering [14] is the best one. The important fact about the Kalman filtering approach is that it can perfectly track the percentage change in amplitude, frequency, and the harmonic content of the abnormal time varying signal in the presence of noise. Taking this advantage into consideration, in this paper we have implemented Kalman filtering for estimation of amplitude, frequency, and phase of the nonstationary signals. The fundamental principle of Kalman Filter approach is described below:

The discrete values of the sinusoidal signal are transformed into a complex vector and modeled along with the frequency in a nonlinear state-space form and the theory of extended Kalman filter is used to obtain the state vectors iteratively. The computation of Kalman gain and choice of initial covariance matrix are crucial in determining the speed of convergence of the new algorithm and its noise rejection property. The characteristic of the model is that 3 states are required to extract the signal frequency, amplitude and phase with the Extended Complex Kalman Filtering. A variety of simulated sinusoids with time varying frequency, amplitude, and phase with noise and harmonics is used for the application of this new technique.

If a sinusoidal signal is sampled with a fixed time interval Δt to produce the sampled set y(k), we get

$$y(k) = A\cos(wk\Delta t + \phi), k = 0,1,2,.... \quad (11)$$

Where w is the frequency of the signal, Δt = sampling interval , A=amplitude, ϕ =phase angle.
The sampled signal x(k) is expressed as

$$y(k) = \frac{A}{2} e^{j\phi}.e^{jw\Delta t} + \frac{A}{2} e^{-j\phi}.e^{-jwk\Delta t} \quad (12)$$

Using the following state variable notations

$$x_1(k) = e^{jwk\Delta t}\ ,\ x_2(k) = A\ ,\ x_3(k) = e^{j\phi} \quad (13)$$

the signal x(k) is modeled in the state space as

$$x_1(k+1) = x_1(k)\alpha$$
$$x_2(k+1) = x_2(k)$$
$$x_3(k+1) = x_3(k)$$
$$\alpha = e^{jw.\Delta t} \quad (14)$$

and the observed signal y(k) is

$$y(k)=\frac{1}{2}x_1(k)x_2(k)x_3(k)+\frac{1}{2}.\frac{x_2(k)}{x_1(k)x_3(k)} \quad (15)$$

The stochastic model of the signal model is obtained

$$\begin{bmatrix} x_1(k+1) \\ x_2(k+1) \\ x_3(k+1) \end{bmatrix} = \begin{bmatrix} \alpha & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1(k) \\ x_2(k) \\ x_3(k) \end{bmatrix} \quad (16)$$

or, $x(k+1)=F.x(k)+v_k$

(17)

The estimated analytic signal is obtained as a function of the states as

$$y(k)=g\{((x_1(k),x_2(k),x_3(k))+\eta(k)\}$$

(18) The above system and applying the EKF technique, a nonlinear recursive filter is obtained for estimating the time varying parameters of a sinusoid embedded in white noise.

$$\hat{x}(k+1)=x(k)+K(k)\left(y(k)-g(\hat{x}(k|k-1)\right)$$

$$\hat{y}(k)=g(\hat{x}(k))+\eta(k) \quad (19)$$

The observation matrix H is obtained as

$$H=\frac{\partial g}{\partial \hat{x}(k)} \quad (20)$$

The observation matrix H is obtained as

H=

$$\begin{bmatrix} \frac{1}{2}x_2(k)x_3(k) & \frac{1}{2}x_1(k)x_3(k) & \frac{1}{2}x_1(k)x_2(k) \\ -\frac{x_2(k)}{2x_1^{\,2}(k)x_3(k)} & +\frac{1}{2x_1(k)x_3(k)} & -\frac{x_2(k)}{2x_1(k)x_3^2(k)} \end{bmatrix} \quad (21)$$

The ECKF measurement update equations are:

$$K(k)=\hat{P}(k/k-1)H^{*T}\left[H\hat{P}(k/k-1)H^{*T}+R\right]^{-1}$$

$$\hat{x}(k/k)=\hat{x}(k/k-1)+K(k)(y(k)-H\hat{x}(k/k-1)$$

$$\hat{P}(k/k)=\hat{P}(k/k-1)-K(k)\,H\,\hat{P}(k/k-1) \quad (22)$$

and the time update equations are:

$$\hat{x}(k+1/k)=F.(\hat{x}(k/k)) \quad (23)$$

$$\hat{P}(k+1/k)=F(k)\,\hat{P}(k/k)\,F(k)^{*T}+Q(k) \quad (24)$$

where $K(k)$= Kalman gain matrix

$\hat{P}(k/k)$ or $\hat{P}(k+1/k)$ = Covariance matrix, R =measurement noise variance, H = Observation vector *, T represent conjugate and transpose of a complex quantity, respectively.

This nonlinear filter is quite stable regardless of the initial conditions of the states x_1 and x_2, and x_3 provided, the observation signal is bounded, which is usually true in a practical system like the power network. After the convergence of the state vector is attained, the frequency is calculated as

$$\hat{f}(k)=\frac{1}{2\pi\Delta T}\sin^{-1}\left[\mathrm{Im}(\hat{x}_1(k))\right] \quad (25)$$

where Im( ) stands for the imaginary part of a quantity.

Further the amplitude of the signal 'A' can be obtained from

$$A=|x_2(k)|\ ,\ \phi=\ln(x_3(k)) \quad (26)$$

5. Computational and Experimental Test Results

Fig. 1 shows the flow chart for the hybrid variable window STFT and Kalman filtering approach to classify the pattern and measure the change in amplitude and frequency, and phase of the pure sinusoidal signal in distorted environment. Different cases of amplitude, phase, and frequency changes are tested using this approach. Test1 analyzes different types of major power quality problems, such as sudden frequency change and harmonic distorted signal, using simulated waveforms and MATLAB software package; Test2 analyzes distorted signals generated using experimental setup. The chosen sampling rate is 2.5 kHz, for Test1 and 2.3kHz for Test2, and the frequency (f) is normalized with respect to a base frequency. The ST output shows the plot of the amplitude contours of a given magnitude in the time–frequency co-ordinate system. The standard deviation (SD) of the contour number 1(having the largest frequency amplitude variation with time) is computed and used to detect the presence of disturbance and its duration is calculated from the change in frequency amplitude of the contour number 1. Further SD indicates whether the disturbance is a steady state short duration disturbance or other high frequency phenomenon. The flow chart shown in Fig.1 clearly indicates that after detection and localization, the Extended Kalman Filter is used to classify and estimate the parameters of the disturbance signal. The following sections provide computational and experimental results:

Test 1:
Computational Results:

To illustrate the application of the hybrid approach, the following case studies are presented:

A. Sudden frequency change

Fig. 2(a) shows the waveform, when the frequency is suddenly reduced from 50Hz to 45 Hz. Such a distorted signal is analyzed by the present approach and the results are plotted as in Fig. 2(b) and Fig. 2(c), respectively. The frequency distortion is reflected in the magnitude of the standard deviation SD which increases from zero to 0.087, and the harmonic factor HF = 0.0285. For this frequency change the time-frequency curve shows localized contours which provide an excellent visual classification. However, with SD > 0.05, the waveform is identified to belong to a class other than voltage sag , voltage swell, or interruption. The Kalman Filter accurately tracks the amplitude of the frequency changes of the original 50 Hz signal.

Frequency Ramping

The frequency of the test sinusoid is allowed to stay at 60 Hz level till 100 samples, and then ramped from 60 Hz to 75 Hz in a span covering 200 samples uniformly. Fig.3 shows the original signal, the S-transform frequency versus time (in samples), the peak magnitude of the signal obtained from the S-transform matrix. From the figure it is quite obvious that the frequency disturbance is completely localized and detected and the peak amplitude of the signal is accurately obtained. The instantaneous frequency estimation is, however, done by the Extended Complex Kalman (ECKF) showing clearly the ramping. The frequency estimation error varies between 0.005 to 0.05 Hz in the presence of noise of 30 dB, SNR. Single step and double step frequency excursions are shown in Figs.5 and 6.

An experimental signal is collected from a signal generator through a data acquisition interface and a software using C^{++} compiler. The initial frequency is 60 Hz and ramped negatively to 45 Hz in a span of 400 samples and then again increases to 60 Hz for the rest of the experiment. The S-transform contours along with the instantaneous frequency tacked by the ECKF are shown in Fig.4. Here again the accuracy is upto .05 Hz in the presence of distortion and noise.

6. Conclusion

This paper introduces the use of ST and Kalman filtering approach as powerful analysis tools that can be used to classify and measure the system response to distorted signals. Using ST, one can detect, localize and visually classify the short duration events in the signal. Then Kalman filtering technique is used to extract important features from the analyzed signal and classify the nature of the disturbance present in the signal. Further the Extended Kalman Filter accurately tracks the change in amplitude, frequency, phase, and harmonic content of the distorted signal. The method is applied on different sets of data obtained from computer simulations and laboratory tests and accurate results are obtained in most of the case studies.

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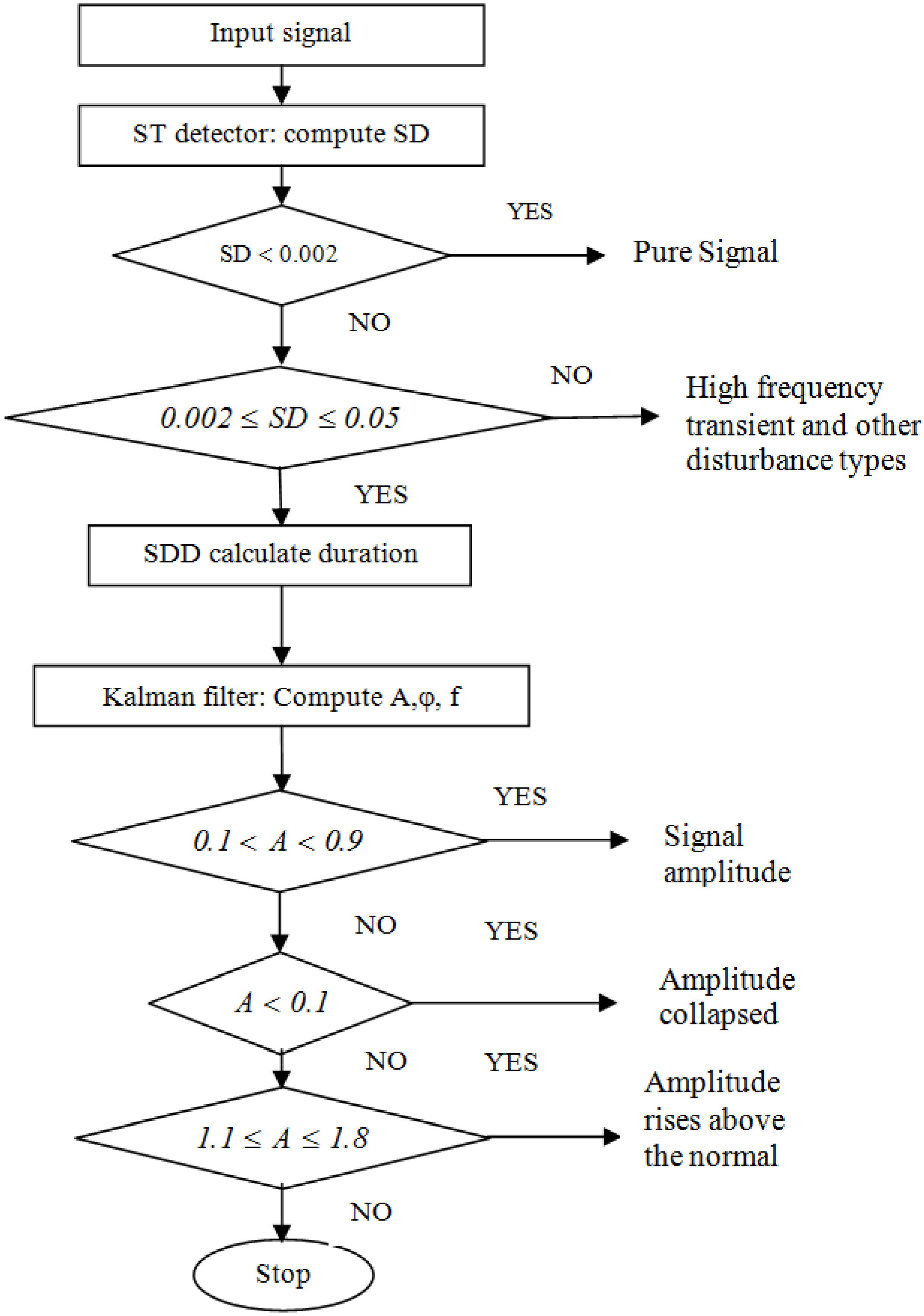


Fig 1. Hybrid S-transform Kalman Filter

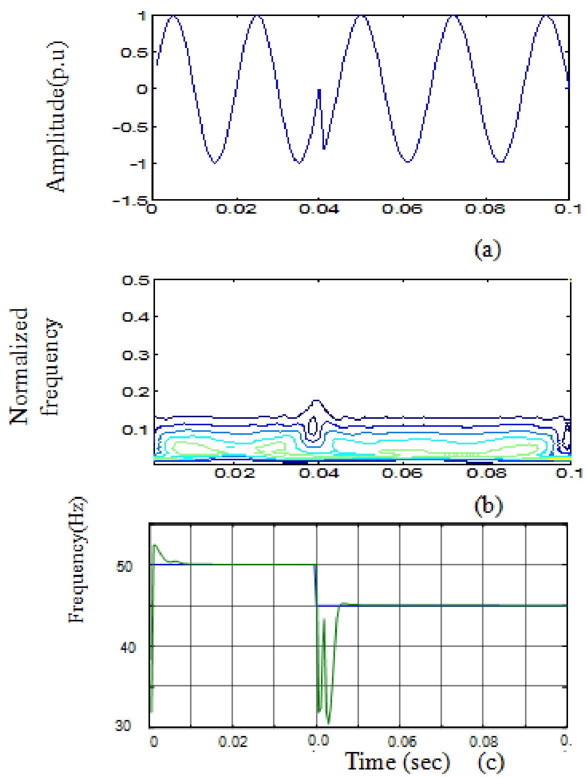
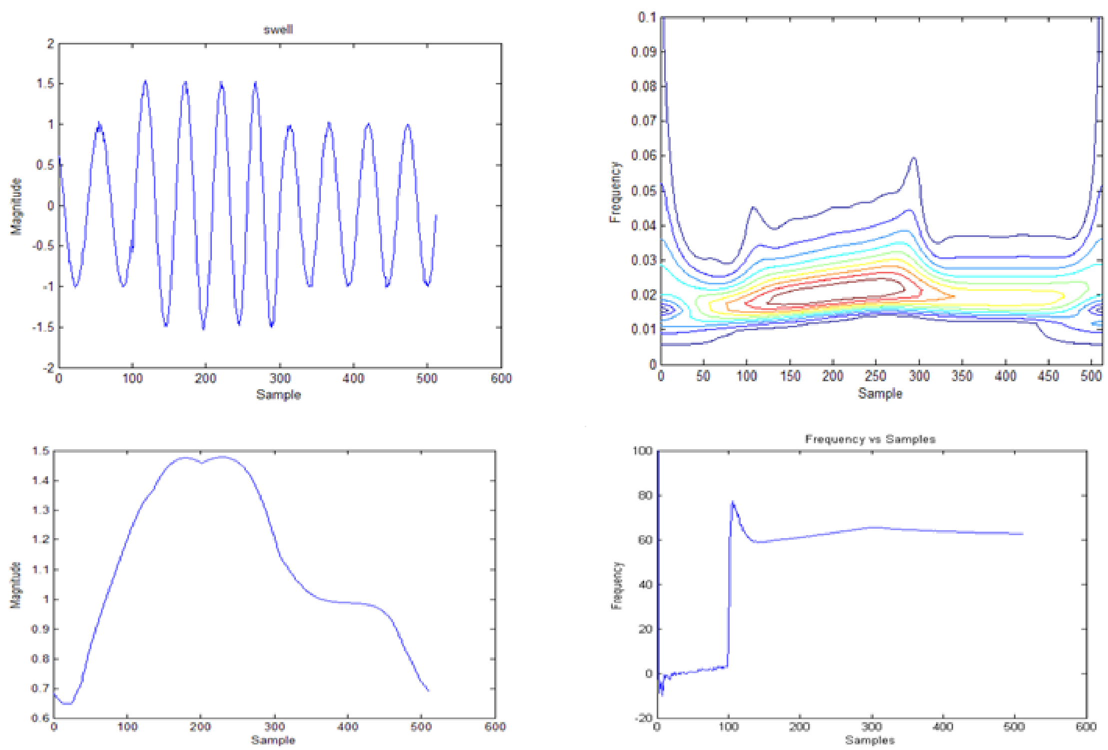
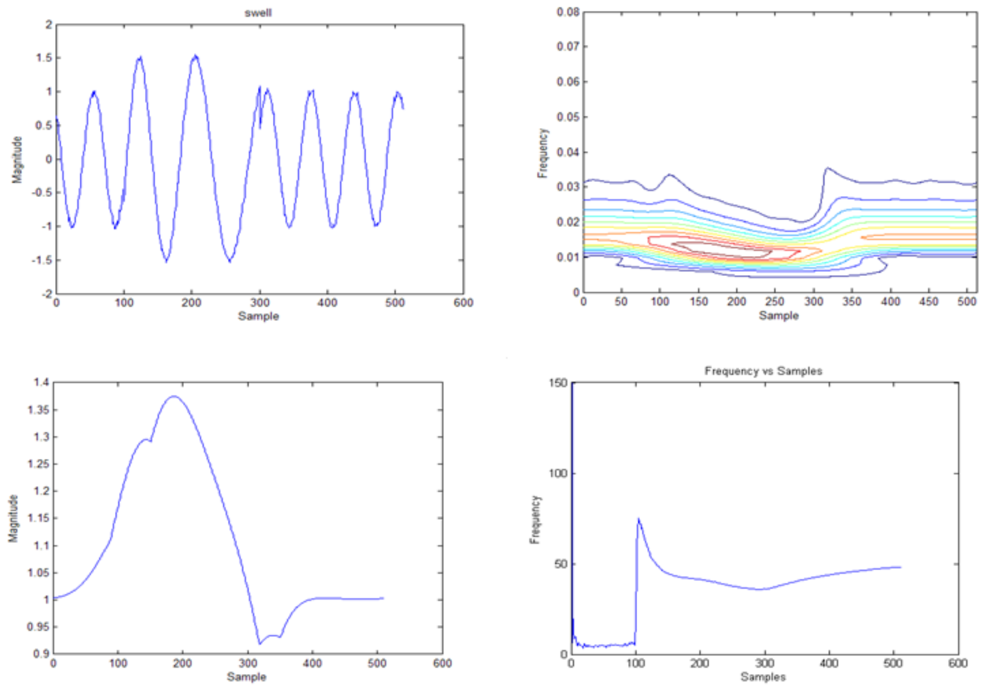


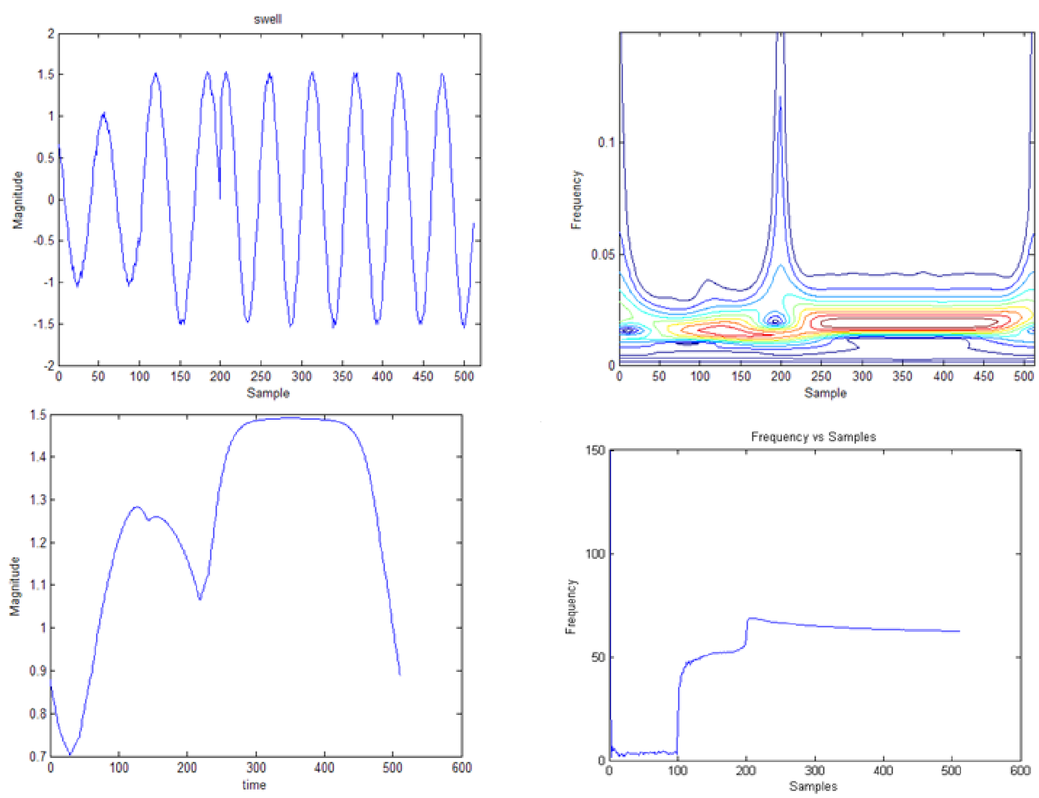
Fig. 2(a) Example of sudden frequency change, (b)S-transform Contour plot, (c)Estimated frequency plot



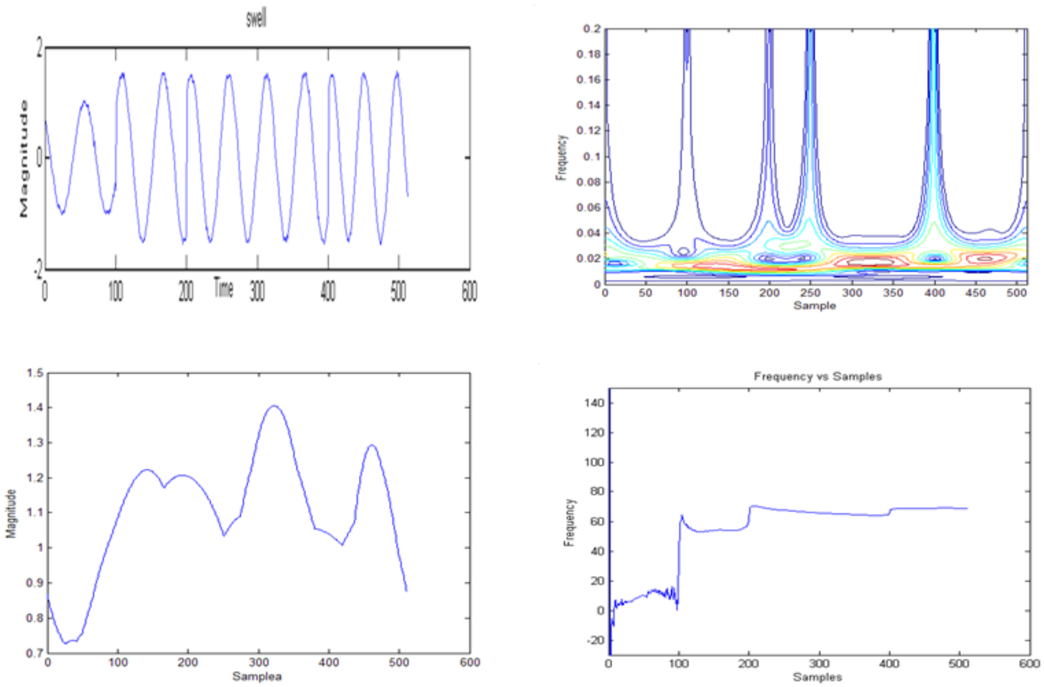
Frequency tracking with CEKF
Fig.3 ramping frequency from 60 to 75 Hz Negative ramp frequency



Frequency tracking with CEKF
Fig.4. Negative ramping frequency



Frequency tracking with CEKF
Fig.5. Single step frequency



Frequency tracking with CEKF
Fig.6. Double step frequency

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