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A modified non-adaptive OSG-SOGI filter for estimation of a biased sinusoidal signal with global convergence properties

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Abstract: This paper presents an algorithm for estimating the parameters of a biased sinusoidal signal. The proposed method uses the output signals of a second order generalized integrator without adaptation on its resonant frequency to derive a linear regression equation where the unknown parameters are a nonlinear combination of bias and frequency of the input signal. The global stability of the method is proven. Remarkably, the proposed method represents the minimum-order estimator known for the problem under consideration, being implementable by a 4th-order adaptive system. Simulation results and comparisons with existing methods show the accurate estimation capability of the proposed approach.

Keywords: Frequency estimation, orthogonal signals generator, second order generalized integrator, adaptive control.

1. INTRODUCTION

The estimation of parameters of a biased sinusoid has always been a topic of considerable research interest in the field of signal processing, mechanical vibrations, control applications. An interesting application is the active noise control Bobtsov and Pyrkin (2012); Fedele and Ferrise (2013, 2014b, 2015); Fedele (2017) in which the objective is to eliminate or significantly reduce the instantaneous noise level, at some location to be made quiet, through destructive interference. Since its key role, the problem of the frequency estimation for a pure sinusoid signal with possibly non-zero mean value, has been widely investigated and many algorithms have been proposed to accomplish this task.

Several studies have explored this topic in depth with the aim of designing both accurate and simple algorithms to be implemented in hardware for real applications. The problem is relevant in the power systems area where a correct synchronization requires the estimation of all parameters of the voltage grid in terms of bias, amplitude and phase angle Fedele et al. (2009); Rodríguez et al. (2007); Liserre et al. (2006); Ghartemani et al. (2011).

The Phase-Locked-Loop (PLL) is a common method to estimate the entire set of parameters. The structure of the main PLL topology is a feedback control system that automatically adjusts the phase of a locally generated signal to match the phase of the input signal. However there is a major inherent issue in the conventional PLL structure. Typically the frequency to be estimated is not constant and when there is frequency fluctuation, the traditional PLL fails to estimate the correct frequency or it exhibits a longer transient time than some fast digital algorithms for instance those based on Fast Fourier Transform. Moreover PLL requires an initial condition, relative to the starting frequency, which has to be close enough to the real one, in order to lock the signal in a fast way. The main difference among single-phase PLL topologies consists in the orthogonal signals generation (OSG) subsystem. Typically, the orthogonal signal generation block is implemented by using Hilbert transform, inverse Park transform, adaptive notch filter, second order generalized integrator (SOGI) Karimi-Ghartemani (2014). In order to deal with the case of biased sinusoid signals, in Ciobotaru et al. (2010) an effective method is used to create orthogonal reference signals based on SOGI according to the information about the signal frequency that can be obtained by using a PLL system in a feedback closed-loop. The reliability of such a

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method has been tested in a wide range of practical scenarios but the dependence on initial conditions of the estimate may limit its use. The algorithm presented in Pigg and Bodson (2009) is based on an enriched PLL scheme that is able to estimate all the parameters of an unbiased periodic signal. In particular, the estimator requires two separate dynamics for the estimation of frequency and amplitude of the signals (plus an additional dynamics for the estimation of the phase angle) with a further parameter designed to adjust the transient of the method, resulting in a more complex scheme to be tuned. Moreover, it is required the generation of explicit sin/cos waves. A modified version of the Enhanced PLL (EPLL) is discussed in Karimi-Ghartemani et al. (2011). EPLL is a special OSG-PLL structure with a high degree of immunity to harmonic and unbalance conditions over conventional PLLs. Moreover it may adapt to frequency variations.

To overcome PLL's drawbacks, frequency-locked-loop (FLL) methods have been introduced as very effective synchronization techniques to be implemented. In addition to the PLL that estimates the phase of the input signal, the FLL estimates also its frequency. FLL techniques have gained much more attention in microgrid control applications motivated by the presence of only one loop for frequency estimation instead of the two loops required by the PLL structures Kherbachi et al. (2019). Moreover FLL systems are less sensitive to phase angle jumps and this is one of the features that make them widely used in real applications. In Rodríguez et al. (2010), for example, a new technique is proposed for detecting frequency harmonics in three-phase systems by using multiple SOGI working together a harmonic decoupling network adapted in frequency thanks to the use of an FLL. A frequency adapted third order generalized integrator (TOGI) is presented in Fedele and Ferrise (2014a); Du et al. (2019) to eliminate the zero drift of the input signal and to achieve frequency adaptive tracking in the case of frequency fluctuations. Unfortunately the formal stability proofs of these methods are based on small-signal analysis or averaging theory. This fact limits the application in real contexts since an unfair choice of the adaptation gains can result in large deviation from the true parameters or may cause instability of the estimator.

Conversely global stability is provided in adaptive observers or nonlinear adaptive systems based method (see Pin et al. (2019) and Pin et al. (2017), respectively with references therein) even if their complexity limits the use in real scenarios.

In order to face with global stability properties of the algorithms based on SOGI, a non-adaptive approach that does not require the continuous adaptation of its resonant frequency is proposed in Fedele and Ferrise (2011); Fedele (2012). Specifically a continuous-time least-squares algorithm is used to estimate both bias and frequency. The remaining parameters are then obtained via simple relationships between the OSG-SOGI output signals. As far as estimator dimension is concerned, the method in Fedele et al. (2009) requires a 7th-order estimation algorithm.

The aim of this paper is to design a parsimonious non-adaptive SOGI filter for the estimation of the entire set of a biased sinusoidal signal parameters. The term *parsimonious* is related to the complexity of the algorithm that requires a number of differential equations equal to the number of parameters to be estimated (this represents in our opinion a low-order algorithm in the plethora of non-adaptive methods based on SOGI). Moreover the global stability properties of the method are discussed by using simple arguments and without invoking complex Lyapunov-based analyses.

The problem is then formulated as follows.

Design a fourth-order algorithm for the estimation of the biased sinusoidal signal

$$v(t) = A_0 + A_c \sin(\rho_c(t))$$

where $\rho_c(t) = \omega_c t + \phi_c$ **is the phase angle and** $\{A_0, A_c, \omega_c, \phi_c\}$ **are the unknown parameters to be estimated.**

The paper is organized as follows: Section 2 presents the SOGI scheme and its main properties; the estimation methods is proposed in Section 3; Section 4 contains some simulated results and comparison with existing methods; the last section is devoted to conclusions.

2. PROPERTIES OF THE SOGI SYSTEM

The method proposed in this note makes use of an orthogonal signals generator based on a second order generalized integrator (OSG-SOGI), see Fig. 1. OSG-SOGI is able to generate the in-phase and the in-quadrature signals, $v_1(t)$ and $v_2(t)$, respectively, when driven by the reference signal $v(t)$ and the parameter α. The SOGI system is governed by the following set of differential equations

$$\dot{v}_1(t) = -\alpha y(t), \quad \dot{v}_2(t) = \alpha v_1(t) \tag{1}$$

where

$$y(t) = v_1(t) + v_2(t) - v(t).$$

The closed-loop transfer functions F_1 and F_2 of the output signal components are given by

$$F_1(s) = \frac{\alpha s}{s^2 + \alpha s + \alpha^2}, \quad F_2(s) = \frac{\alpha^2}{s^2 + \alpha s + \alpha^2}$$

such that $v_i(s) = F_i(s)v(s)$, for $i \in \{1, 2\}$.

In contrast to usual frequency-adaptive SOGI methods, where the filter parameter α corresponds to the estimated frequency adapted by using frequency-locked-loop blocks Fedele et al. (2009), in this case α is kept constant and equal to a user-defined value. In this setting, the SOGI system (1) can be seen as a pre-filter producing auxiliary signals $v_1(t)$ and $v_2(t)$, that will be used later for adaptation. This structure of the estimator is also known as 'prefiltering-based' (see Chen et al. (2015), Pin et al. (2013)), in view of the fact that a linear time-invariant filter is applied the measured signal to derive useful auxiliary signals that allow to streamline the design of the adaptive estimator. Compared to the pre-filtering methods Chen et al. (2015), Pin et al. (2013), the proposed algorithm uses a SOGI prefiltering stage that yields a reduced-order filter. Nonetheless, the tunable adaptation law described later will permit to tune the noise sensitivity, thus achieving a noise-immunity comparable to the aforementioned methods despite the complexity reduction.

It is straightforward to note that F_1 is a second-order band-pass filter with the cut-off frequency α. At the resonant frequency there is no attenuation and the phase is equal to zero; instead there is a quite large attenuation outside the resonant frequency. Moreover $F_2(s)$ represents a second-order low-pass filter so it has no attenuation and phase equal to $-\pi/2$ at the resonant frequency. High values of α will provide to quickly reach the steady-state conditions for the output signals $v_1(t)$ and $v_2(t)$. As it is evident, the output $v_2(t)$ is affected by the presence of the offset which does not appear in $v_1(t)$ because of the derivative action on the input signal $v(t)$. Therefore, the generated signal $v_1(t)$ and the input $v(t)$ are in-phase and with the same amplitude when the SOGI resonant frequency is equal to frequency of the input signal.

As a consequence, if the frequency ω_c of the input signal $v(t)$ is equal to the resonant frequency α of the OSG-SOGI, the signal $v_1(t)$ tends to the unbiased signal

$$\lim_{t\to\infty} v_1(t) = v(t) - A_0$$

while the signal $v_2(t)$ tends to the input signal $v(t)$ with a phase shift of $\pi/2$:

$$\lim_{t\to\infty} v_2(t) = v\left(t - \frac{\pi}{2}\right).$$

It is worth pointing out that when the input voltage is corrupted by disturbances such as harmonics below the cut-off frequency or a DC-offset, the low-pass filter F_2 does not reject them sufficiently. As a result, the orthogonal component $v_2(t)$ may contain part of these disturbances and will be shifted by an amount of the input DC-offset. Consequently, a trade-off between frequency selectivity and response speed should be adopted. The use of the OSG-SOGI as sinusoid signal tracking strongly depends on the frequency input α, thus problems can occur when signal frequency has fluctuations. In order to adjust the OSG-SOGI resonance frequency, in many cases its structure is coupled with an adaptive tuning algorithm Fedele and Ferrise (2014a).

The idea exploited in the next section is to design a parsimonious method (in terms of the minimum-order estimator known for the considered problem) to estimate the unknown parameters of the biased sinusoid independently by the choice of the resonant frequency α.

3. ESTIMATION METHOD

The proposed FLL filter representing the OSG-SOGI and the adapting strategy for parameters estimation is depicted in Fig. 1. The input signal $v(t)$ is the biased sinusoid

$$v(t) = A_0 + A_c \sin(\omega_c t + \phi_c)$$

where $\theta = \{A_0, A_c, \omega_c, \phi_c\}$ is the set of unknown parameters to be estimated. It is effortless to show that $v_1(t)$ and $v_2(t)$ converge to the following steady-state signals Fedele (2012):

$$v_{1\infty}(t) = m_1 A_c \sin(\omega_c t + \phi_c + \phi), \tag{2}$$

$$v_{2\infty}(t) = A_0 - m_2 A_c \cos(\omega_c t + \phi_c + \phi) \tag{3}$$

where

$$m_1 = \frac{\alpha\omega_c}{\sqrt{(\alpha^2-\omega_c^2)^2 + \alpha^2\omega_c^2}},\ m_2 = m_1\frac{\alpha}{\omega_c}$$

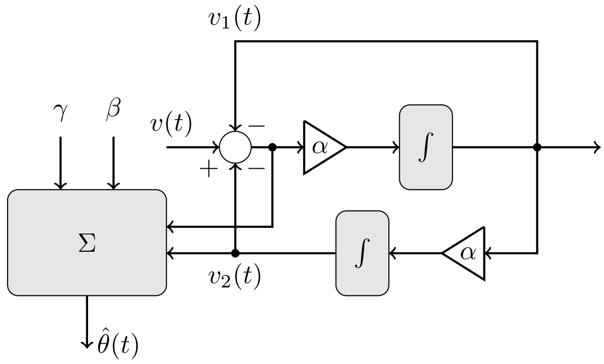

Fig. 1. Frequency-Locked-Loop filter based on a non-adaptive SOGI prefiltering stage.

and

$$\phi = sgn(\alpha - \omega_c)\frac{\pi}{2} - \arctan\left(\frac{\alpha\omega_c}{\alpha^2-\omega_c^2}\right).$$

Therefore, ignoring the transient terms that converge to zero exponentially fast, at steady state the following relation holds

$$h(t) = \phi(t)^T\theta^*$$

with

$$h(t) = \alpha^2 y(t),$$

$$\phi(t) = \begin{bmatrix} -1 \\ v_2(t) \end{bmatrix}$$

and

$$\theta^* = \begin{bmatrix} A_0\omega_c^2 \\ \omega_c^2 \end{bmatrix}. \tag{4}$$

One way to generate an estimate $\hat{\theta}(t)$ of θ^* is to minimize the instantaneous cost criterion

$$J(\hat{\theta}) = \frac{1}{2}\left(\alpha^2 y(t) - \phi(t)^T\hat{\theta}(t)\right)^2$$

by using the gradient descent method

$$\dot{\hat{\theta}} = -\gamma\nabla J(\hat{\theta})$$

where $\gamma > 0$ is the adaptive gain and $\nabla J(\hat{\theta})$ is the gradient of J with respect to $\hat{\theta} = \begin{bmatrix} \hat{g}_1 \\ \hat{g}_2 \end{bmatrix}^T$.

This procedure leads to the adaptive law

$$\begin{aligned} \dot{\hat{g}}_1(t) &= -\gamma\left(\alpha^2 y(t) - v_2(t)\hat{g}_2(t) + \hat{g}_1(t)\right) \\ \dot{\hat{g}}_2(t) &= -\dot{\hat{g}}_1(t)v_2(t) \end{aligned} \tag{5}$$

implemented in the block Σ.

Lemma 1. The vector of regressors

$$\phi(t) = \begin{bmatrix} A_0 + A_1\sin(\omega t + \phi) \\ A_2 \end{bmatrix}$$

with $A_i \in \mathbb{R}$, $i = 0, 1, 2$ and $A_1, A_2 \neq 0$ is persistently exciting.

Proof. Note that

$$H = \int_{t_0}^{t_0+\frac{2\pi}{\omega}} \phi(\tau)\phi(\tau)^T d\tau = \frac{2\pi}{\omega}\begin{bmatrix} A_0^2 + \dfrac{A_1^2}{2} & A_0A_2 \\ A_0A_2 & A_2^2 \end{bmatrix}.$$

It follows that $H = H^T > 0$ and $H \geq \lambda_{min}(H)\mathbb{I}_2$, where $\lambda_{min}(H)$ is the minimum eigenvalue of H and $\mathbb{I}_2$ is the 2-dimension identity matrix.

By invoking Theorem 3.6.1 of Ioannou and Fidan (2006) and thanks to the persistent exciting property of the regressors stated by Lemma 1, it is straightforward to prove that the algorithm based on (1) and (5) enjoys global-exponential convergence to θ^*.

Therefore, the unknown parameters A_0 and ω_c can be estimated by (4) as

$$\hat{\omega}_c(t) = \sqrt{\hat{g}_2(t)},$$
$$\hat{A}_0(t) = \frac{\hat{g}_1(t)}{\hat{g}_2(t)}, \quad \text{if } \hat{g}_2(t) > \delta$$

where $\delta > 0$ is a user-defined threshold constant used to avoid divisions by zero in the algorithm.

Given the estimate of A_0 and ω_c, the amplitude A_c is estimated as

$$\hat{A}_c = \sqrt{\frac{v_{1\infty}(t)^2 + \frac{\hat{\omega}_c(t)^2}{\alpha^2}\zeta(t)^2}{m_1^2}}$$

where

$$\zeta(t) = v_{2\infty}(t) - \hat{A}_0(t).$$

Moreover the phase angle of the sinusoidal signal can be estimated as

$$\hat{\rho}_c(t) = \arg\eta(t) - \phi$$

with

$$\eta = -\frac{\hat{\omega}_c(t)^2}{\alpha^2}\zeta(t) + j\frac{\hat{\omega}_c(t)}{\alpha}v_{1\infty}(t).$$

A slight modification of the adaptive law (5) is here proposed. Let us consider

$$\bar{g}_2(t) = \frac{1}{\beta}\hat{g}_2(t) \tag{6}$$

with $\beta \in (0, 1)$.

Therefore the cost criterion (3) is rewritten as

$$J(\bar{\theta}) = \frac{1}{2}\left(\alpha^2 y(t) + \hat{g}_1 - \beta\bar{g}_2(t)v_2(t)\right)^2 \tag{7}$$

and the adaptive law becomes

$$\begin{aligned}\dot{\hat{g}}_1(t) &= -\gamma\left(\alpha^2 y(t) - \beta v_2(t)\bar{g}_2(t) + \hat{g}_1(t)\right)\\ \dot{\bar{g}}_2(t) &= -\beta\dot{\hat{g}}_1(t)v_2(t).\end{aligned} \tag{8}$$

The use of the adaptive law (8) instead of (5) is instrumental in reducing the noise on the estimated frequency, as it will be clear in the simulated experiments.

4. NUMERICAL SIMULATIONS

In this section some numerical simulations are reported to highlight the characteristics of the proposed methods. Comparisons with existing techniques are conducted according to the following criteria: the considered methods and the proposed one are firstly tuned up in order to present similar convergence rates and then tested, with the same parameter settings, introducing variations on the input signal. Input signals, sampled with a period of $T_s = 3 \times 10^{-4}s$ are affected by a zero mean Gaussian noise with a signal-to-noise ratio (SNR) equal to 10. The SNR is measured in decibels as the logarithm of the average power of the reference signal samples and the noise ones, i.e. $w(\cdot)$, over the experiment time as

$$SNR \triangleq 10\log_{10}\left(\sum_{k=0}^{n-1} v(kT_s) / \sum_{k=0}^{n-1} w(kT_s)\right)$$

where n is the number of samples.

Example 1. In this example, the considered input signal is $v(t) = 2 + 10\sin\left(\int \omega_c(\tau)d\tau + \frac{\pi}{3}\right)$ where

$$\omega_c(t) = \begin{cases} 4, \ 0 \le t < 30, \\ 6, \ 30 \le t < 60, \\ 2, \ 60 \le t < 90. \end{cases}$$

The input frequency is then affected by two frequency steps and the frequency estimated by the proposed method, denoted by (**FPP**) in the figures, is compared with the ones obtained by the modified PLL in Karimi-Ghartemani et al. (2011) (**GKJBM**) and with the active notch filter described in Aranovskiy et al. (2010) (**ABKNS**) with a correction term that guarantees the boundedness of the generated signals. All the considered methods are firstly simulated with noise-free data to set the free parameters. The GKJBM algorithm is set up with $k = 1.6$, $k_0 = 0.1$ and $\gamma_g = 0.1$ while ABKNS parameters are $k = 1$, $\alpha = 1$ and $\theta_0 = 50$. The FPP filter is tuned with $\alpha = 8$, $\beta = 0.08$ and $\gamma = 1.8$. The same initial frequency condition for all methods is $\hat{\omega} = 3.2$. The frequency estimations performed by the considered algorithms are reported in Fig. 2. All the methods deal with the first two steps in a satisfactory manner but GKJBM presents oscillations around the actual frequency in the third sweep. Moreover, the proposed method presents a slowdown compared to the tracking performances of the previous sweeps. It is worth to underline that such a behavior is strictly related to the choice of the parameter set $\{\alpha, \beta, \gamma\}$. In particular the larger the parameter β the faster is the transient response. Unfortunately, the choice of the parameter β is a trade-off between two opposing effects: a fast transient and the sensitivity to noise affecting the signal; this behaviour will be better highlighted in the following simulations.

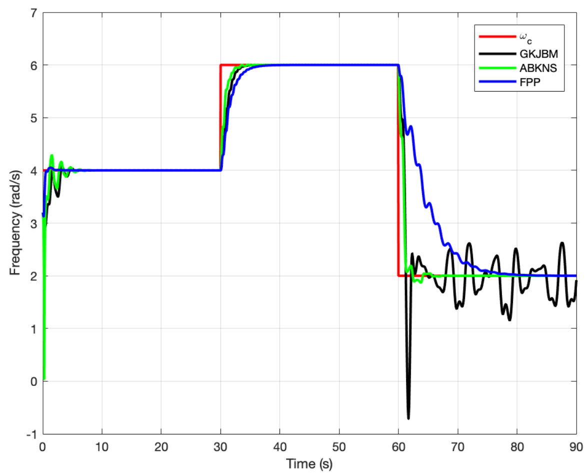

Fig. 2. Example 1. Frequency estimation with no noisy signal.

Fig. 3 shows the frequency estimations in the case of noisy signal. As it can be noted the proposed method performs a satisfactory filtering action. ABKNS degrades its performance in this case although it can be improved by an accurate choice of the gain parameters at the expense of longer transients. The performance of GKJBM is also affected in terms of frequency deviation. Both GKJBM and FPP are able to reconstruct the input signal, each with its own peculiarities, as shown in Fig. 4. ABKNS is able to estimate bias, amplitude and frequency only.

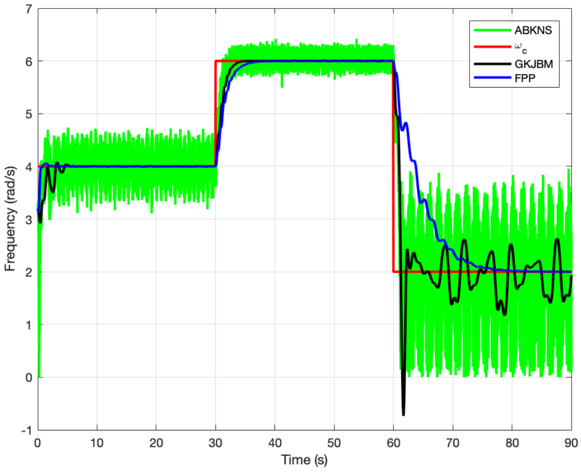

Fig. 3. Example 1. Frequency estimation with noisy signal.

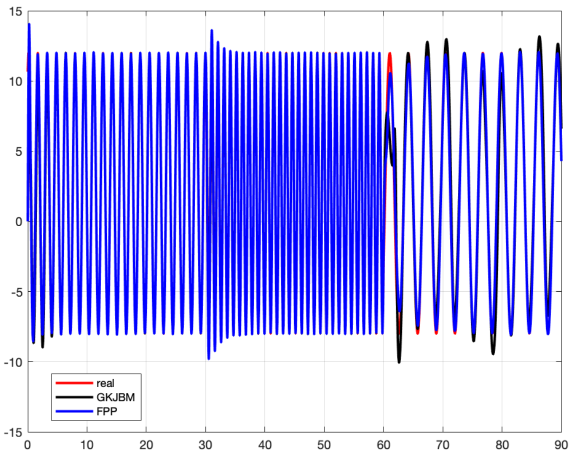

Fig. 4. Example 1. Input signal reconstruction.

Example 2. In this example the following frequency sweep is considered

$$\omega_c(t) = \begin{cases} \dfrac{2}{45}t + 4, & 0 \le t < 45, \\ -\dfrac{2}{45}t + 8, & 45 \le t < 90. \end{cases}$$

All other settings are the same as in the previous experiment. Fig. 5 show the frequency estimation of the considered algorithms. A data window showing the reconstruction of the input signal is reported in Fig. 6.

Example 3. This example aims at highlighting the properties of the frequency estimation related to the choice of the parameter β in Eqs. (6)-(8). The proposed method is applied to the estimation of the parameters of the biased sinusoidal signal

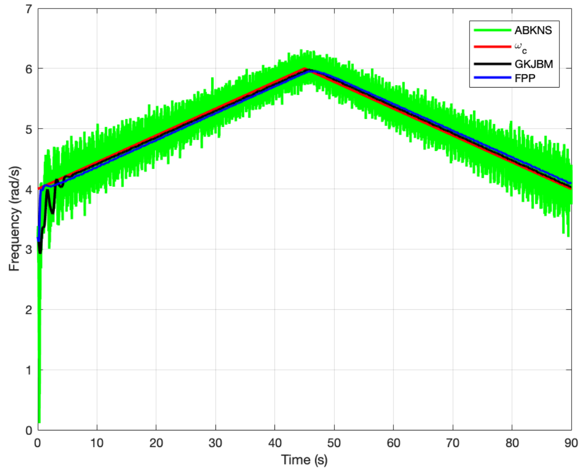

Fig. 5. Example 2. Frequency estimation with noisy signal.

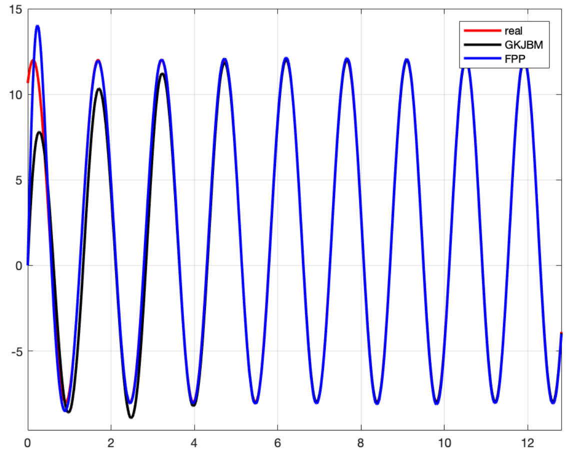

Fig. 6. Example 2. Input signal reconstruction.

$$v(t) = 2 + 10\sin\left(4t + \frac{\pi}{3}\right), \quad 0 \le t < 90$$

corrupted with noise ($SNR = 10$). Three simulations are conducted considering the same input signal with different values of the parameter β. The other parameters are the same of previous examples. Fig. 7 shows the frequency estimations with $\beta = 0.02, 0.05, 0.1$. As expected by increasing the value of β the convergence speed of the method increases too, at the cost of an increased noise sensitivity.

5. CONCLUSIONS

In this paper, a method for the on-line estimation of the frequency, amplitude, phase and offset of a biased sinusoidal signal has been proposed. The discussed approach is based on a non-adaptive second order generalized integrator, i.e. its resonant frequency is not adapted but a-priori fixed in order to have an acceptably fast steady-state response. The method is parsimonious in the sense that it is able to estimate all the four parameters of a biased sinu-

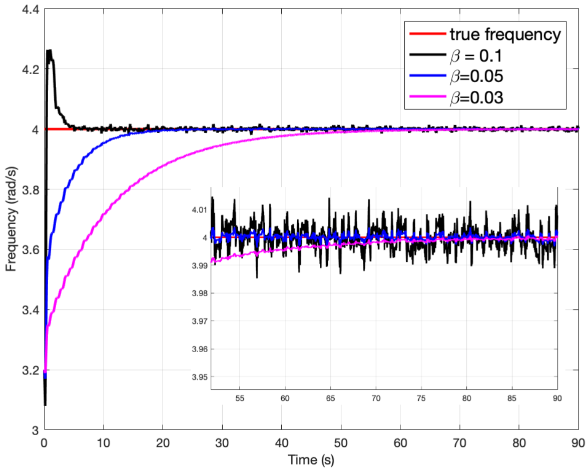

Fig. 7. Example 3. Frequency estimation varying the parameter β.

soidal signal by a fourth order complexity. Simulations and comparisons with existing methods have been conducted in order to illustrate the reconstruction capability of the method also in the case of typical time-varying frequency such as frequency step and sweep variations.

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