Adaline-based approaches for time-varying frequency estimation in power systems

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Abstract: Two new neural approaches for on-line frequency estimation of a sinusoidal signal perturbed by harmonic distortions and random noise are presented in this paper. These approaches are based on an iterative formulation of the signal which is learned by Adaline neural networks. Adalines are very simple and efficient artificial neural networks, they can be easily implemented on a digital signal processor. The proposed approaches are therefore suitable for real-time implementations and their performance and robustness are evaluated by numerical simulations and experimentally under different severe operating conditions. The proposed neural estimators are favorably compared to the classical zero-crossing method, to an active notch filter method, and to a previous Adaline based-method. Furthermore, all these methods are also evaluated in terms of computational costs.

Keywords: frequency estimation, frequency tracking, Adaline, artificial neural networks, power distribution network.

1. INTRODUCTION

On-line frequency estimation of sinusoidal signals is a classical problem and has many practical applications. Frequency of power system voltages and currents is for example a key parameter in supervising and controlling the quality of the delivered power (Arrillaga and Watson, 2003). In this application, it is imperative to precisely know the fundamental frequency and the harmonics parameters such as their magnitude and phase. Efficient filters can thus be designed for compensating for the harmonic distortions (Ould Abdeslam et al., 2007).

Many algorithms have been proposed to evaluate the frequency content from discrete time samples of a measured signal. Most of them are frequency domain harmonic analysis algorithms and are based on the Discrete Fourier Transform (DFT) or on the Fast Fourier Transform (FFT). These methods however suffer from three main drawbacks, aliasing, leakage and picket-fence effect (Joorabian et al., 2009). To overcome them, the Fourier algorithm can be associated to a Zero-Crossing (ZC) technique (Djuric and Djuric, 2008). Combining both methods allows to provide the fundamental frequency of a measured signal corrupted by higher-order harmonics.

The ZC-technique is a simple and well-known method which can be used as a standalone frequency estimator. Its principle relies on calculating the number of cycles within a predetermined time interval. However, this method is sensitive to noise and is often combined with other methods like least squares algorithms (Sadler and Casey, 2000).

Kalman or extended Kalman filters are other important alternatives for frequency estimation. In (Dash et al., 1999), an extended Kalman filter is based on a state space formulation of a three-phased voltage vector obtained with the well-known αβ-transform. Nevertheless, Kalman filtering for frequency estimation is really efficient only with three-phase signals.

Phase-Locked Loops (PLLs) are also well-known signal processing techniques used for frequency measurement. In (Akagi et al., 2007) for example, a PLL has been developed for three-phase signals. This PLL is based on a fictitious instantaneous active power expression and allows frequency estimation, under distorted and unbalanced voltage waveforms. It determines automatically the system frequency and the phase angle of the fundamental positive-sequence component of a three-phase generic signal even under highly distorted and perturbed system voltages.

Frequency estimation can also be achieved through an Adaptive Notch Filter (ANF). An ANF is a second-order notch filter that is further furnished with a nonlinear differential equation to update the frequency. In (Karimi-Ghartemani et al., 2005), an ANF is adapted and inserted in the context of power systems. The proposed ANF is used for estimation of power system frequency and its performance is compared with that of a PLL approach.

Recently, Artificial Neural Networks (ANNs) approaches have been developed for on-line frequency estimation. Hopfield neural networks, i.e., a type of recurrent ANN, have been successfully employed in (Lai et al., 1999). Adaline-based approaches have also been proposed (Dash et al., 1997; Ai et al., 2007). Whatever the architecture, ANNs have to be appropriate for a real-time frequency evaluation. The neural network implementation, but also the computational costs of the learning algorithm, must be compliant with the real-time constraint of this application.
This paper introduces two original approaches for the time-varying frequency estimation of a single signal highly distorted by random noise and harmonics. Based on an Adaline neural network, an iterative formulation of the signal is proposed and learned. The Adaline is fast and simple, its weights update algorithm allows to compute the true frequency between two successive acquisition of the measured signal. In the first approach, a single Adaline extracts the frequency from learning from a pseudo-squared signal. In the second approach, several Adalines are used and a Multi-Layer Perceptron (MLP) selects the one with the best frequency estimation. This leads to accurate and robust approaches which can be implemented using microprocessors or Digital Signal Processing (DSP) boards.

In Section 2, the learning and modeling of a sinusoidal signal with an Adaline is briefly described. This forms the foundation of the two original neural approaches introduced in Section 3. In Section 4, the proposed methods are evaluated and compared to other well-known methods in terms of precision, robustness and computational costs in estimating the frequency of a signal disturbed by significant noise and harmonic distortions. Conclusions are provided in Section 5.

2. ADALINE FOR FREQUENCY ESTIMATION

The objective is to estimate on-line the fundamental frequency of a single sinusoidal signal corrupted by noise and harmonic distortions. One of the possible applications is to estimate the fundamental frequency in power distribution systems.

On-line frequency estimation is a challenging problem without any knowledge and hypothesis about the signal. Indeed, the signal is characterized by several parameters, i.e., the amplitude, frequency and phase of every harmonic component. Furthermore, it is possible to assume that these parameters can independently vary at every moment, changing thus the harmonic content of the signal. Without loss of generality, we propose to develop a frequency estimator which is not sensitive to the phase and amplitude of the measured signal. We also assume that the signal can be considered as having a sinusoidal waveform, i.e., is composed of a significant and varying fundamental frequency component, of other harmonic distortions and of random noise.

We propose to develop a frequency estimator based on an Adaline neural network because of its simplicity and learning capabilities. An Adaline is a very simple ANN which can be considered as a linear combiner that outputs the weighted product of its inputs. The weights of the Adaline are adapted and can be interpreted due to its structure. Indeed, its weights can be interpreted as physical parameters of the system or of the relation between its inputs and outputs. Basically, this is not the case for other types of ANNs (Haykin, 1999).

2.1 A previous Adaline-based method

The Adaline has been introduced for frequency estimation by (Dash et al., 1997). The approach has been used since (Ai et al., 2007) to identify the parameters of the following discrete signal model:

\[
y(k) = A \sin(\omega k T_s + \phi)
\]

where \(A\) represents the amplitude of the signal \(y(k)\), \(\omega\) its angular frequency, \(\phi\) its phase and \(T_s\) is the sampling time. From there, it is possible to define the next and previous samples:

\[
y(k+1) = A \sin(\omega k T_s + \omega T_s + \phi) = A \sin(\omega k T_s + \phi) \cos(\omega T_s) + \cos(\omega k T_s + \phi) \sin(\omega T_s),
\]

\[
y(k-1) = A \sin(\omega k T_s - \omega T_s + \phi) = A \sin(\omega k T_s + \phi) \cos(\omega T_s) - \cos(\omega k T_s + \phi) \sin(\omega T_s).
\]

By combining expressions (2) and (3), a recursive expression of the discrete signal can be deduced:

\[
y(k+1) + y(k-1) = 2 \cos(\omega T_s) y(k),
\]

and therefore

\[
y(k) = 2 \cos(\omega T_s) y(k-1) - y(k-2).
\]

This expression can be learned by an Adaline. The previous measures of the signal, i.e., \(y(k-1)\) and \(y(k-2)\), serve as inputs of the Adaline. A constant term is added as an input, it serves as a bias. The input vector of the Adaline is thus \(x = [y(k-1) y(k-2) 1]^T\). The Adaline outputs the following estimation of the signal:

\[
\hat{y}(k) = w^T x = [w_0 \ w_1 \ w_2] [y(k-1) \ y(k-2) \ 1]^T.
\]

Due to this architecture, the Adaline’s weights \(w = [w_0 \ w_1 \ w_2]^T\) are enforced to converge to an optimal solution \(w^* = [2 \cos(\omega T_s) -1 \ a_{dc}]^T\) in order to fit in with (5). The term \(a_{dc}\) represents the amplitude of a dc-component. The Adaline’s output is compared to the signal \(y(k)\) at each sampled time. The error \(e(k) = y(k) - \hat{y}(k)\) is used to correct the Adaline weights with a Least Mean Squares (LMS) algorithm at each iteration (Haykin, 1999).

According to the optimal weight \(w^*\), the fundamental frequency \(f = \omega/(2\pi)\) is extracted from the weight \(w_0\) at each time sample \(k\):

\[
f(k) = \frac{1}{2\pi T_s} \arccos \left( \frac{w_0(k)}{2} \right).
\]

Furthermore, the weight \(w_1\) has to converge toward -1 and can be used to evaluate the quality of the convergence. This architecture is shown by Fig. 1. One of its advantages is its immunity to the amplitude and phase of the signal.
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3. NEW ADALINE-BASED METHODS FOR FREQUENCY ESTIMATION

The robustness of the Adaline in estimating the power system frequency has been addressed. This analysis leads to the development of two new methods also based on Adalines for frequency tracking. One approach is based on several Adalines, the second one uses only one Adaline with a preprocessed signal instead of the rough signal.

3.1 The MAdaline approach

The Adaline approach delivers a good and fast estimation of a precise frequency with an appropriate sampling period. Now, the idea is to use one Adaline in a small frequency range, each with its own virtual sampling period. As the fundamental frequency is supposed to vary around a precise value, the range around this value is divided in small ranges. An Adaline is assigned in each of these small ranges, and the following sampling periods are then used in their respective algorithms for delivering the frequency estimation: $T_{si} = 1/(4f_i)$ with $f_i$ the central frequency of the $i$-th frequency range. We chose for example to cover the range $[47, 53]$ Hz with 30 Adalines yielding 0.2 Hz per Adaline.

In this approach, each Adaline produces a different estimation of the fundamental frequency and the one with the best response has to be picked. Different selection algorithms and approaches have been evaluated for this, from the Adaline’s convergence test (based on its weight $w_1$ which has to converge toward -1) to more sophisticated ones. The best results have been obtained with a MLP. The inputs of this ANN are the five last values of the weight $w_1$, i.e., $w_1(k)$ to $w_1(k - 4)$ of each Adaline, which means a total 150 inputs. The outputs are 30 binary
signals corresponding to the 30 Adaline. The hidden layer is composed of 60 neurons with a sigmoid function. Finally, the $150 \times 60 \times 30$ MLP learns with a conventional backpropagation algorithm (Haykin, 1999) the ability of an Adaline to deliver the best estimation of the frequency at a given instant $k$.

3.2 The pseudo-square Adaline

The effect of a small frequency deviation is nearly insignificant in only one period of the signal. It is therefore very difficult to provide a precise estimation of its instantaneous deviation. The idea now consists first in increasing the effect of the frequency deviation within a period and to use thereafter the Adaline-based method. This can be achieved for example by using the square of the measured signal. The result is thus a signal with a frequency which is the twice of the original. Using only the instantaneous signal also amplifies the noise effect from a precise instant. Accordingly, our approach consists in using the product of the instantaneous signal with a passed value of the signal delayed by $d$ sampling periods:

$$
\Psi(k) = y(k) y(k - d)
$$

$$
= A \sin(\omega k T_s) \sin(\omega k T_s - \omega d T_s)
= A^2 \sin^2(\omega k T_s) \cos(\omega d T_s)
- A^2 \sin(\omega k T_s) \sin(\omega d T_s) \cos(\omega k T_s)
= \frac{A^2}{2} (1 - \cos(2\omega k T_s)) \cos(\omega d T_s)
- \frac{A^2}{2} \sin(2\omega k T_s) \sin(\omega d T_s).
$$

The coefficients are $\alpha = \cos(\omega d T_s)$ and $\beta = \sin(\omega d T_s)$. By using $d = 1/(4f) = \pi/(2\omega)$, the coefficients can be simplified respectively by $\cos(T_s \pi/2)$ and $\sin(T_s \pi/2)$. With $T_s = 5 ms$, $\alpha$ is close to 1 and $\beta$ is close to 0 which means that the second part of (9) can be neglected compared to the first part. Expression (9) can thus be simplified by:

$$
\Psi(k) \approx \frac{A^2}{2} (1 - \cos(2\omega k T_s)).
$$

An Adaline can be used to learn the digital signal $\Psi(k)$ from (10) with three inputs, $[\Psi(k - 1), \Psi(k - 2), 1]$. The frequency can be extracted from the weight $w_0$, $w_1$ has to converge toward -1 and $w_2$ toward the dc-component of the signal. The principle is illustrated by Fig. 4.

![Fig. 4. Principle of the pseudo-square Adaline](image)

Fig. 4. Principle of the pseudo-square Adaline

shows a heavily distorted signal and the waveforms of its instantaneous square and of its pseudo-square $\Psi(k) = y(k) y(k - d)$ with $d = 1/(4f)$. Furthermore, Fig. 6 shows the frequency spectrum of the signal only after sampling and of its pseudo-square. One can see that higher-order harmonic distortions are filtered and the fundamental frequency of $\Psi(k)$ which is $2f$.

4. RESULTS AND COMPARISONS

The proposed methods have been evaluated in simulation and experimentally. Moreover, their results are compared to the results obtained with other methods, i.e., the ZC method, the ANF method and the original Adaline-based method.

We first used a simulated signal heavily distorted by both harmonics and noise. The signal is composed of a fundamental component mixed with harmonics of rank 2, 3, 4 and 5 having respectively an amplitude of 1%, 20%, 1% and 5% of the fundamental component. This signal also contains an additional Gaussian noise with a 30 dB Signal to Noise Ratio (SNR).

![Fig. 5. Appearance of a pseudo-squared signal (bottom) containing harmonic distortions (top)](image)

![Fig. 6. Frequency spectra of the signal containing harmonic distortions and of its pseudo-square](image)
The behavior of the different methods in estimating the changing fundamental frequency is shown by Fig. 7 and Fig. 8. The estimation of the pseudo-square Adaline is represented by Fig. 7 but also on each plot of Fig. 8 in addition to the estimation of another approach, i.e., the original Adaline, the MAdaline approach, the ZC method and the ANF method. Table 1 gives the Mean Absolute Error (MAE) between the exact and the estimated frequency for each approach during a constant increase and after an abrupt change of $f$. The mean delay and convergence time obtained with each method are also provided. Methods with the best performance are the ZC method and the pseudo-square Adaline. The ANF method is more precise than the MAdaline approach which although reduces the MAE by 2 compared to the original Adaline method.

The robustness of the methods is evaluated with a signal containing much more harmonics:

$$s(k) = \sin(\omega kT_s) + \gamma \sum_{n=2}^{19} \frac{1}{n!} \sin(n\omega kT_s). \quad (11)$$

![Fig. 7. Pseudo-square Adaline frequency estimation](image)

![Fig. 8. Frequency estimation with 4 methods: a) original Adaline, b) MAdaline, c) ZC method, d) ANF method](image)

![Fig. 9. Sensitivity of the frequency estimators to the amplitude of the harmonic components](image)

![Fig. 10. Sensitivity of the frequency estimators to the amplitude of the prime number harmonics](image)

Table 1. Performances of the different frequency estimation methods

<table>
<thead>
<tr>
<th>Methods</th>
<th>MAE (0.5 to 1 s.)</th>
<th>mean delay (1 to 1.5 s.)</th>
<th>MAE convergence (ms)</th>
<th>time (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>original Adaline</td>
<td>0.402</td>
<td>59.1</td>
<td>0.567</td>
<td>120</td>
</tr>
<tr>
<td>pseudo-square Adaline</td>
<td>0.157</td>
<td>31.3</td>
<td>0.122</td>
<td>80</td>
</tr>
<tr>
<td>MAdaline (30)</td>
<td>0.237</td>
<td>59.4</td>
<td>0.242</td>
<td>80</td>
</tr>
<tr>
<td>ZC method</td>
<td>0.131</td>
<td>14.5</td>
<td>0.118</td>
<td>30</td>
</tr>
<tr>
<td>ANF method</td>
<td>0.182</td>
<td>15.0</td>
<td>0.217</td>
<td>40</td>
</tr>
</tbody>
</table>

The influence of the harmonics are analyzed by changing the value of the gain $\gamma$ in (11). Results are presented by Fig. 9 where the MAE is represented for each method when $\gamma$ varies from 0 to 2. The ZC method is the only method which is not sensitive to the harmonics increase. It should be mentioned that $\gamma = 2$ represents very severe conditions in practical applications. The same evaluation has been achieved but only with prime number harmonics which is most representative of a power distribution signal. Results are shown by Fig. 10. It can be seen that the ZC method and the pseudo-square method are very less sensitive than all the other methods. Additionally, the noise influence has been investigated and the results are presented by Fig. 11. In this figure, the MAE of each method is represented according to a SNR varying from 10 to 100 dB. A low ratio means that the signal is clearly readable. The performance of the ZC method is better than the performances of the other methods when the SNR increases. One can seen that the MAE of the ZC method and the pseudo-square method is important when the SNR is small. The MAE remains constant for each method for a SNR varying from 40 to 100 dB.

Moreover, the pseudo-square Adaline can work properly compared to conventional methods. It has shown the good performance and robustness of the Adaline at each sampling time. The estimators have been verified in numerical simulations and experimentally to learn an iterative expression of the sampled signal.

This paper proposes two new neural approaches for estimating time-varying frequency in power systems in real-time. These approaches are based on Adaline neural networks with an optimized sampling period. The method that is called the MAdaline approach is based on Adalines estimating the frequency with different values of the sampling time and a MLP learns and choses the best response. The method which is called the pseudo-square Adaline relies on a single Adaline using the product of the instantaneous signal with a delayed value. Both approaches are linear regression techniques that allow approximating time-varying frequency in power systems in real-time. These approaches are based on Adaline neural networks.

The different methods are also compared in terms of computational costs. Table 2 shows the number of delay blocks, operations and functions involved in each method. This has been achieved in order to optimize their real-time implementation on a DSP board. Indeed, the methods have been implemented on a dSPACE board in order to estimate the frequency of a real signal. Conditions representative of a power distribution system have been used and similar conclusions have been deduced. According to its robustness with harmonics and noise, the pseudo-square method represents the best compromise whatever the conditions. The MAdaline approach represents a good alternative only when the SNR is very low and if the computational requirements are available.

5. CONCLUSION

Table 2. Computational costs of the different frequency estimation methods

<table>
<thead>
<tr>
<th>methods</th>
<th>delay blocks</th>
<th>multiplication</th>
<th>addition</th>
<th>division</th>
<th>function</th>
</tr>
</thead>
<tbody>
<tr>
<td>original Adaline</td>
<td>2</td>
<td>15</td>
<td>10</td>
<td>3</td>
<td>1 × arccos</td>
</tr>
<tr>
<td>pseudo-square Adaline</td>
<td>3</td>
<td>16</td>
<td>10</td>
<td>3</td>
<td>1 × arccos</td>
</tr>
<tr>
<td>MAdaline (30)</td>
<td>60</td>
<td>691</td>
<td>11040</td>
<td>91</td>
<td>1 × arccos</td>
</tr>
<tr>
<td>ZC method</td>
<td>7</td>
<td>2</td>
<td>6</td>
<td>4</td>
<td>1 × sign</td>
</tr>
<tr>
<td>ANF method</td>
<td>3</td>
<td>8</td>
<td>5</td>
<td>0</td>
<td>-</td>
</tr>
</tbody>
</table>

With a high level of harmonic distortions and noise. Results and computational costs show that this neural method is well adapted for a real-time implementation on DSP devices.

REFERENCES


