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A ZERO CROSS DETECTION METHOD FOR AC POWER CONVERTERS BASED ON AN EXTENDED KALMAN FILTER

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A Zero Cross Detection method for AC power converters based on an Extended Kalman Filter

We disclose a new method for the joint detection of phase, frequency and amplitude of AC line voltage that can outperform existing solutions in terms of detection precision and robustness to noise and distortions on the AC line. This method is a fundamental building block in digitally controlled AC/AC power converters, allowing them to operate with a tight adaptation to the input AC voltage, which in turn brings more efficiency, more precise output control, and less conversion outages due to input AC variations.

The method is based on digital processing of the AC input voltage signal by matching it to an AC line model using an Extended Kalman Filter approach. The estimated state of the model provides a joint estimation of the phase, frequency and amplitude of the input AC signal, and a detection of Zero Cross events. These outputs are then used for the driving of the switching devices of an AC power converter.

The architecture of our method is depicted in **Figure 1**. The input AC voltage is digitally sampled at a suitable constant frequency (e.g., 20kHz). We define a state vector including the phase, frequency and amplitude, and consider a state evolution model based on a sinusoidal waveform with unknown frequency and amplitude, including process noise as well as measurement noise. Based on these, we derive the formulas for the prediction and the update steps of an Extended Kalman Filter that takes an initial arbitrary estimation of the state vector and refines it iteratively, finding the state vector value that best approximates the input AC waveform. In a typical operation scenario, the frequency and amplitude state variables will converge to the frequency and amplitude of the input AC signal, whereas the phase will evolve at each iteration, accurately following the phase of the input AC signal. Zero cross events are detected when the phase value matches 0 and 180 degrees.

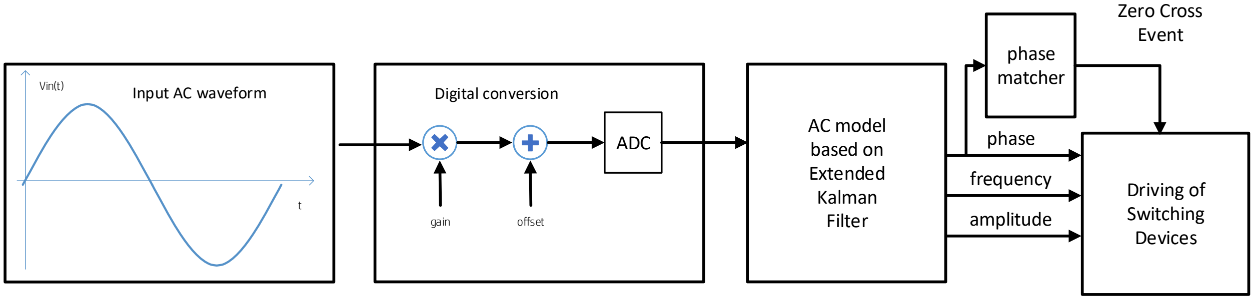

Figure 1: architecture of the proposed method

The AC model based on the Extended Kalman Filter, which is the core of the proposed solution, is described in the following.

Let T_s be the ADC sampling time.

Let k be the discrete time index associated with each ADC sample.

We define the state vector

$$x_k = [\theta_k \quad f_k \quad a_k]$$

Where:

- θ_k is the phase of the AC input in radians
- f_k is the frequency of the AC input
- a_k is the amplitude of the AC input

We use the standard filtering notation, according to which the predicted value of x is denoted as $\hat{x}$, the subscript $k|k-1$ denotes the prediction at time k using the measurements up to time $k-1$, and the subscript $k|k$ denotes the prediction at time k using the measurements up to time k.

The general process equation (a.k.a. state prediction) is

$$x_{k|k-1} = F_{k-1} x_{k-1|k-1} + \nu_k$$

where F_{k-1} is the state evolution matrix, and ν_k is the process noise.

The predicted state $\widehat{x}_{k|k-1}$ is determined by the process process equation

$$\widehat{x}_{k|k-1} = F_{k-1} \widehat{x}_{k-1|k-1} + \nu_k$$

For our ZCD model, we choose

$$F_{k-1} = \begin{bmatrix} 1 & 2\pi T_s & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

This yields:

- $\hat{\theta}_{k|k-1} = \hat{\theta}_{k-1|k-1} + 2\pi T_s \hat{f}_{k-1|k-1}$
- $\hat{f}_{k|k-1} = \hat{f}_{k-1|k-1}$
- $\hat{a}_{k|k-1} = \hat{a}_{k-1|k-1}$

The general form of the observation equation is

$$y_{k|k-1} = h_k\left(x_{k|k-1}\right) + n_k$$

For our ZCD model, we define the estimated observation $\widehat{y}_{\,k|k-1}$ as

$$\widehat{y}_{\,k|k-1} = \hat{a}_{k|k-1}\cos(\hat{\theta}_{k|k-1})$$

The predicted error covariance matrix $P_{x,k|k-1}$is calculated as

$$P_{x,k|k-1} = F_{k-1}P_{x,k-1|k-1}F_{k-1}^T + Q_k$$

Note that for our model the process equation is linear. This allows us to use F_{k-1}in the above, like we would do for a normal Kalman filter. A general extended Kalman filter would instead use a jacobian matrix.

The covariance innovation matrix $P_{y,k|k-1}$is calculated as

$$P_{y,k|k-1} = \widetilde{H}_k P_{x,k|k-1}\widetilde{H}_k^T$$

Where $\widetilde{H}_k$ is the jacobian of the observation equation, given by

$$\widetilde{H}_k = \nabla h_k(x_k)|_{\widehat{x}_{\,k|k-1}}, \quad \nabla = \left[{}^{\partial}/_{\partial x_1} \quad \cdots \quad {}^{\partial}/_{\partial x_N}\right]$$

For our ZCD model, we have

$$\widetilde{H}_k = \begin{bmatrix} -\hat{a}_{k|k-1}\sin\left(\hat{\theta}_{k|k-1}\right) \\ 0 \\ \cos\left(\hat{\theta}_{k|k-1}\right) \end{bmatrix}^T$$

The Kalman gain K_k is calculated as

$$K_k = P_{x,k|k-1}\widetilde{H}_k^T P_{y,k|k-1}^{-1}$$

The updated state is calculated as

$$\widehat{x}_{\,k|k} = \widehat{x}_{\,k|k-1} + K_k(y_k - \hat{y}_{k|k-1})$$

And the updated error covariance as

$$P_{x,k|k} = P_{x,k|k-1} - K_k\widetilde{H}_k P_{x,k|k-1}$$

This concludes the operations at time k. Then, $k = k + 1$, and the above steps are repeated.

For the measurement noise covariance, we use

$$R_k = \sigma_{V_{in}}$$

Which can be pre-determined or easily estimated from measurements.

The process noise covariance Q_k represents the covariances of

$$\nu_k = \begin{bmatrix} \nu_k^{\theta} \\ \nu_k^{f} \\ \nu_k^{a} \end{bmatrix}$$

Q_k could be estimated from test vectors or using the Autocovariance Least Squares methods.

Upon completion of each step, the updated state vector contains the estimated phase, frequency and amplitude of the input AC signal. Zero cross events are detected when the state phase is equal to 0 and π.

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