Feature Extraction Algorithm for Power Quality Disturbance Signals using Least Mean Square Filter


[1] Ph.D Scholar, Department of Electrical Engineering, Annamalai University, [2] Professor, Department of Electrical Engineering, Annamalai University

Abstract—Power quality is an important parameter in power system monitoring, control and protection. The estimation of the features of power quality disturbance signals plays an important role in power quality assessment and power flow control. A Least Mean Square (LMS) algorithm in complex form is presented in this paper to extract the features of power quality disturbance signals where the formulated structure is very simple. To enhance the convergence characteristic of the complex form of the LMS algorithm, a variable adaptation step-size is incorporated. The performance of the proposed algorithm is studied through simulations at different situations of the power quality disturbance signals.

Index Terms—Feature extraction, least mean square, power quality, power system monitoring.

I. INTRODUCTION

Power quality (PQ) disturbances such as voltage sags, swells, interruptions, flicker and harmonic distortion may lead to mal-operation or failure of any sensitive electric facilities such as computer based processor or automatic system. The critical aspect of PQ studies is the ability to perform PQ data analysis and classification. The important step in understanding and hence improving the quality of electric power is to extract sufficient information about the events that cause the PQ issues. A number of papers based on different techniques for detection and classification of power quality phenomena have been published over the past years. Some survey studies can be found in [1-3]. Therefore, the features of power signal is an important parameter in power system relaying, power-quality monitoring, and operation and control of devices using digital technologies.

Available feature estimation techniques, in general, use digitized samples of system voltage. Considering the power system voltage waveform as purely sinusoidal, the time between two zero crossings is an indication of system frequency. However, in reality, the measured signals are available in distorted form and, thus, a number of techniques are available for feature estimation. Discrete Fourier transform, least error square, Kalman filtering, orthogonal finite-impulse-response (FIR) filtering, and iterative approaches [4-7] are some of the important techniques in this area. Soft computing techniques, such as neural network and genetic algorithms (GAs), are also utilized for feature extraction of power quality disturbance signals [8-9].

The least mean square (LMS) algorithm is widely used in signal processing applications as an adaptive filtering technique since its introduction by Widrow and Hoff [10]. The LMS technique as such possesses the advantages of simplicity in its underlying structure, computational efficiency, and robustness. In this paper, an LMS-based feature extraction technique is proposed which uses the voltage signal. A complex signal, for the LMS algorithm, is derived from the three-phase voltages by the transform [10]. As the signal in the model is complex, the LMS algorithm applied is in complex form [11]. However, such an algorithm suffers the problem of poor convergence rate as the adaptation step-size is fixed.

To overcome this, time varying step-size is usually employed in the standard LMS algorithm [12]. Still, the approach is sensitive to noise disturbance which is expected in a power system environment. Therefore, in this work, an algorithm with variable step-size, adjusted in accordance with the square of the time-averaged estimate of the autocorrelation of successive error samples [13], is used. Such an algorithm has the advantage of better immunity against noise disturbance. The performance of the proposed feature extractor is adjudged through different voltage signals.

After the introduction, a brief description of the LMS algorithm with its mathematical formulation is presented in Section 2, while in the Section 3 explains the LMS based feature extraction and its algorithmic steps to extract the magnitude and slope from the voltage signals. Simulation studies are presented in Section 4. Finally, the conclusion is drawn in the last Section.

![Least Mean Square Filter](image)

Fig. 1. Least Mean Square Filter

II. LMS ALGORITHM

The LMS method of signal feature extraction is depicted in Fig. 1, where \( y_t \) denotes the actual signal, \( \hat{y}_t \) denotes the signal estimate and \( X_t = [x_{0t}, x_{1t}, \ldots, x_{N-1}]^T \) is the input vector at the \( t \)th instant. The signal can be estimated correctly by the filter with a suitable value of its coefficient \( W_0 \), which is obtained through minimizing the squared of the error signal \( e_t \) [13]. Thus the framework gains knowledge from its condition; this is represented as a tuned filter where the filter coefficients are adapted in a recursion manner towards their optimal esteems. At
every iteration, the weight vector \( W_t \) is calculated as,
\[ W_{k+1} = W_k + \mu (-\nabla_k) \]  
where \( \mu \) is the adaptation parameter, \( W_i = [w_0, w_1, ..., w_{n-1}]^T \) is the filter coefficient and \( \nabla_i \) is the gradient of the error performance surface with respect to filter coefficient, this can be calculated as,
\[ \nabla_k = -2 \epsilon_k \tilde{X}_k \]  
The recursion (1) is called the LMS algorithm and it is initialized by setting all coefficients to zero. Then the technique continues by calculating the error signal \( \epsilon_k \), then it is employed to calculate the adapted coefficients. This process is executed till the stable conditions are achieved. The stableness of the closed loop network is administered by the parameter \( \mu \) and it ought to fulfill the following criteria,
\[ 0 < \mu < \frac{2}{\text{Total input power}} \]  
where \( \mu \) is the step size of the algorithm.

### III. LMS Based Feature Extraction

The voltage signal of a three phase electrical network can be presented in discrete mode as,
\[ V_{ak} = V_m \cos (ak \Delta t + \varphi) + \epsilon_{ak} \]
\[ V_{bk} = V_m \cos (ak \Delta t + \varphi - \frac{2\pi}{3}) + \epsilon_{bk} \]
\[ V_{ck} = V_m \cos (ak \Delta t + \varphi + \frac{2\pi}{3}) + \epsilon_{ck} \]  
where \( V_m \) is the maximum magnitude of the fundamental component, \( \epsilon_k \) is the noise present in the voltage signal, \( t \) is the sampling time, \( \varphi \) is the phase of fundamental component, and \( \omega \) is the angular frequency of the voltage signal (\( \omega = 2\pi f \), with \( f \) being the system frequency). The complex form of signal derived from the three phase voltages is obtained by \( a\beta \) transform [14] as mentioned as follows,
\[ \begin{bmatrix}
  V_{ak} \\
  V_{bk} \\
  V_{ck}
\end{bmatrix}
= \begin{bmatrix}
  1 & -\frac{1}{2} & -\frac{1}{2} \\
  \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \\
  0 & \frac{1}{2} & -\frac{1}{2}
\end{bmatrix}
\begin{bmatrix}
  V_{ak} \\
  V_{bk} \\
  V_{ck}
\end{bmatrix}^T 
\]  
A complex voltage can be obtained from above as
\[ V_k = V_{ak} + jV_{bk} \]  
The voltage \( V_k \) can be modeled as
\[ V_k = A e^{j(\omega k \Delta t + \varphi)} + \xi_k \]  
where \( A \) is the amplitude of the complex signal \( V_k \), and \( \xi_k \) is its noise component \( \tilde{V}_k = A e^{j(\omega k \Delta t + \varphi)} \). The voltage can be modeled as
\[ \tilde{V}_k = \tilde{V}_k + j \xi_k \]  
where \( \tilde{V}_k \) is the complex weight vector \( W_k \) at every sampling time as,
\[ W_k = W_{k-1} + \mu_k \epsilon_k \tilde{V}_k^* \]  
where \( * \) represents the complex conjugate of the value and \( \mu \) is the convergence factor controlling the stability and convergence rate of the technique.

The step size \( \mu_k \) is varied as in [13] for better convergence of the LMS algorithm in the presence of noise. For complex states, the equations can be updated as,
\[ \mu_{k+1} = \lambda \mu_k + \gamma p_k p_k^* \]  
where \( p_k \) represents the autocorrelation of \( e_k \) and \( e_{k-1} \) is computed as
\[ p_k = \rho p_{k-1} + (1 - \rho) e_k e_{k-1} \]  
where \( \rho \) is an exponential weighting factor and \( 0 < \rho < 1 \), \( 0 < \lambda < 1 \) and \( \gamma > 0 \) controlling the speed of convergence. \( \mu_{k+1} \) is set to \( \mu_{max} \) or \( \mu_{min} \) when it goes above or below the upper and lower limits correspondingly. These values are chosen based on signal statistics described in [13].

The voltage magnitude \( A_t \) is instantly calculated at any time sample \( t \) from the evaluated esteem of voltage \( \tilde{V}_t \) as,
\[ A_t = |\tilde{V}_t| \]  
The slope \( S_t \) is calculated as follows,
\[ S_t = \frac{(A_t - A_{t-1})}{\sqrt{t}} \]  
where \( A_t \) and \( A_{t-1} \) are the voltage magnitudes at the time interval \( t \) and \( t+1 \) respectively.

### IV. Simulation Results

The LMS algorithm uses voltage samples to derive a complex form of voltage for estimating the features. When the signal contains a significant amount of harmonic components, a pre filter is necessary which introduces around half a cycle delay in the estimation process. In high voltage systems, such contamination may not be significant and in such situations, there will be no need for pre filtering. A sampling rate of 5 kHz is required for the filter and the online computation burden is quite less compared to most of the other feature extractor of power quality signal. In this work, power quality distortions signals are five voltage signal distortions admitting sag, swell, outage, surge and harmonic distortions [16]. These voltage distortions are produced by using MATLAB software as per the simulation test network shown in Fig. 3.

The simulation test network comprises of a generator providing the power to the distribution system that contains a short transmission line section and three loads such as normal, heavy, and nonlinear loads at the point of common coupling (PCC). Each generated signal comprises of 25 cycles of a voltage waveform sampled at a rate of 6.4 kHz, which is equal to 128 samples per cycle. The following simulation analyses are proposed to outline the performance and efficiency of the presented method. The heavy and nonlinear loads are
interconnected to the network through a circuit.

A. Pure Sinusoidal Voltage

The pure sinusoidal voltage sag measured at power transmission line is depicted in Fig. 4a. The magnitude and the slope outputs from the LMS filter are depicted in Fig. 4b and c.

B. Voltage Sag

Voltage sag is a reduction of 10–90% of the rated bus voltage for duration of 0.5 cycles to 1 min. The voltage sag is produced by the event of a single line to ground fault for 10 cycles at the terminal of the transmission lines. The exponential decaying voltage sag from 0.2 sec to 0.4 sec at power transmission line is depicted in Fig. 5a. The magnitude and the slope outputs from the LMS filter are depicted in Fig. 5b and c.

C. Voltage Swell

On account of voltage swell, there is an ascent of 10–90% in the voltage magnitude for 0.5 cycles to 1 min. The swell is produced by detaching the substantial load for 10 cycles. The exponential decaying voltage swell from 0.2 sec to 0.4 sec at power transmission line is depicted in Fig. 6a. The magnitude and the slope outputs from the LMS filter are depicted in Fig. 6b and c.
D. Voltage Outage

An outage might be viewed as lost of voltage on the network. Such distortion depicts a drop of 90–100% of the rated bus voltage for duration of 0.5 cycles to 1 min. A waveform of the exponential decaying voltage outage produced by a 10 cycle three phase short circuit fault from 0.2 sec to 0.4 sec at PCC is depicted in Fig. 7a. The magnitude and the slope outputs from the LMS filter are depicted in Fig. 7b and c.

E. Voltage surge

The surge happens on unplugging the substantial load for one quarter cycle as depicted in Fig. 8a and b, where the magnitude is all of a sudden raised from 1 to 3 p.u. The sudden change in voltage waveform from 0.2 sec to 0.21 sec at PCC is depicted in Fig. 8a. The magnitude and the slope outputs from the LMS filter are depicted in Fig. 8b and c.

F. Voltage harmonic

Distortion of the voltage waveform is produced by interconnecting the nonlinear load for 10 cycles where the harmonic is produced. The disturbance waveform is depicted in Fig. 9a. Such a harmonic disturbance waveform is validated using the presented method and the LMS filter outcomes are depicted in Fig. 9b and c.

The tracking error of LMS filter is observed to be under 0.5%. The tracking error depicts the measured voltage magnitude using LMS filter. If the magnitude is assessed with high precision and minimum tracking error, the slope is precisely assessed.
**CONCLUSION**

This paper proposes a new feature extraction technique for the power system environment using LMS filter. The LMS based approach using sampled values of three phase voltage signals is simple in its formulation. The LMS algorithm in complex form uses a time varying step size adjusted in accordance with the square of a time averaging estimate of the consecutive error samples. Test results show that the accuracy and speed of estimation is satisfactory even in the presence of noise/harmonics and during frequency variation. Other important advantages of the algorithm are its simplicity in formulation and computational efficiency. Data collected from the power system are also used to test the validity of the algorithm.

**REFERENCES**


