Power quality disturbance classification using Hilbert transform and RBF networks

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ABSTRACT

This paper presents the application of Hilbert transform and artificial neural network (ANN) for power quality (PQ) disturbance classification. The input features of the ANN are extracted from the envelope of the disturbance signals by applying Hilbert transform (HT). The features obtained from the Hilbert transform are distinct, understandable and immune to noise. These features after normalization are given to the radial basis function (RBF) neural network. The data required to develop the network are generated by simulating various faults in a test system. The performance of the proposed method is compared with the existing feature extraction techniques in combination with other ANN architectures. Simulation results show the effectiveness of the proposed method for power quality disturbance classification.

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1. Introduction

The quality of electric power has become an important issue for electric power utilities and its customers. As a result, power quality (PQ) research is gaining interest. Degradation in quality of electric power is normally caused by power-line disturbances such as voltage sag, swell, momentary interruption, flicker, notch, transients and harmonics. These disturbances result in malfunctions, reduced life time and failure of electrical equipment. In order to determine the sources and causes of power quality disturbances, we must be able to detect and classify the disturbances into different types.

The major requirement in power quality study is the ability to perform automatic power quality monitoring and data analysis. Feature extraction is a vital step in automatic disturbance waveform classification. Spectral analysis using discrete Fourier transform (DFT) and fast Fourier transform (FFT) [1] have been applied for this purpose, but due to the non-stationary nature of the power quality disturbances such transforms are not effective in detecting the disturbance waveforms.

Wavelet transform [2] has been proposed to detect and classify various types of power quality disturbances. The wavelet analysis expands the signal in terms of wavelets, which are generated in the form of translations and dilations of a fixed function called the mother wavelet. Wavelet transformation has the ability to analyze different power quality problems simultaneously in both time and frequency domains. Gaouda et al. [4] proposed an effective wavelet multi-resolution signal decomposition method for analyzing the power quality transient events based on the standard deviation and root mean square value. Huang and Jou [5] proposed an arithmetic coding approach based on wavelet packet transform to compress the power quality disturbance data in their paper. Since noise is omnipresent in a real electrical power distribution network, Yang and Liao [6] presented a de-noising scheme for enhancing wavelet-based power quality monitoring system. In this scheme, Gaussian white noise is considered and a threshold to eliminate the noise influence is determined adaptively according to the background noise.

Gaing [2] has proposed a combined wavelet transform and probabilistic network (PNN) approach for disturbance waveform classification. In this approach, energy distribution at 13 decomposition levels of wavelet and time duration of each disturbance are taken as features of the network. A self organizing learning array system based on wavelet transform has been presented in [3] for the classification of power quality disturbances. The features are obtained by calculating the energy at each decomposition level.

Although wavelet transform has the capability to extract features from the signal in both time and frequency domain simultaneously and has been applied in the detection and classification of power quality, it exhibits some disadvantages [3] like excessive computation, sensitivity to noise level and the dependency of its accuracy on the chosen basis wavelet.

Mishra et al. [7] has proposed S-transform approach for feature extraction in disturbance waveform classification. In this approach, the features of the network are extracted from the
frequency and phase contours of the S-matrix of the signal. Lee [11] has presented S-transform based intelligence based system for classification of power quality disturbance signals in which the change in energy and standard deviation calculated from the S-transform of the contour is considered as a feature to the network. Samantaray et al. [13] employed S-transform based statistical techniques for the analysis of power quality disturbances.

In this paper, Hilbert transform (HT) has been proposed for feature extraction. Hilbert transform transforms the real data sequence into an analytical signal which has a real part, that contains the original data, and an imaginary part, which contains the Hilbert transform. The imaginary part is a version of the original real sequence with a 90° phase shift. Sines are, therefore, transformed to cosines and vice versa. The Hilbert transformed series has the same amplitude and frequency content as the original real data and includes phase information that depends on the phase of the original data. The Hilbert transform is useful in calculating instantaneous attributes of a time series, especially the amplitude and frequency. The advantage of Hilbert transform over wavelet transform is that it avoids the requirement of testing various families of wavelets so as to identify the best one for the accurate classification. Further, the decomposition of the disturbance signals at different resolutions is not required in the Hilbert transform, thereby reducing the memory size and computational overhead. Abdel-Galil and Sadaany [15] proposed the Hilbert transform for the analysis of flicker signal. In paper [16], the authors applied the Hilbert transform for calculating the envelope of the flicker signal. Yu et al. [17] employed Hilbert transform based spectrum analysis for the analysis of mechanical signals. Oin et al. [18] used Hilbert transform based envelope detection and instantaneous frequency estimation technique for the fault diagnosis of mechanical signals and in paper [19], the authors used Hilbert transform based spectral estimation techniques for the analysis of mechanical signals.

Classification is another major task in power quality recognition. Most of the authors have used feed forward neural networks with sigmoidal nonlinearities [12] for model development. The short coming of this network is that it takes long time for training. Also, it has no inherent ability to detect the outliers. In this paper, we propose RBF networks [8] to recognize the disturbance waveform. RBF networks takes less time for training and the distance-based activation function used in the hidden nodes gives the ability to detect the outliers during estimation. Vasilic and Kezunovic [14] proposed the Fuzzy ART neural networks for the analysis of and classification of power system faults.

2. Proposed methodology

The proposed methodology for disturbance waveform classification is based on artificial neural network. Artificial neural network approach for any application involves two stages: network development and actual usage of the network. The various stages involved in the network development are:

- data generation,
- feature extraction and
- network training

Generation of the appropriate training data is an important step in the development of ANN models. A large number of training data is generated through off-line simulation process. Five types of power quality disturbances namely normal, sag, swell, harmonics, transients and voltage flicker along with normal signal are generated.

Feature extraction is the most important component of designing the automatic disturbance waveform classification system. The feature extractor should reduce the dimension of the input pattern (i.e., the original waveform) while retaining most of the useful information from the original signal. In this work, the features of the disturbance waveform are extracted by finding the envelope of the signal using Hilbert transform and applying standard statistical techniques.

The extracted features are presented to the neural network for training. During the training stage, the network captures the relation between the input features and the output class. After training, network is tested with the test data to assess the generalization capability of the network. The details of the Hilbert transform and RBF neural network are given in the subsequent sections.

3. Feature extraction using Hilbert transform

The discrete Hilbert transform [15] is a mathematical tool used to generate an analytical signal from real signal. It is obtained by convolving the real signal \( x(t) \) with the function \( 1/\pi t \) as given below:

\[
x_{\text{H}}(t) = x(t) \frac{1}{\pi t} = \frac{1}{\pi} \int_{-\infty}^{\infty} x(\lambda) (t - \lambda) d\lambda
\]

where \( \lambda \) is the shifting operator.

The analytical signal provides the information about the amplitude as well as the phase of the signal.

Since the output of the DHT is, in fact 90° phase shifted version of the original signal \( x(t) \), a complex signal (also known as analytical signal) that is associated with the original signal can be constructed as

\[
x[k] = x[k] + jx_{\text{H}}[k]
\]

The envelope of the signal is defined as

\[
|x[k]| = \sqrt{x^2 + x_{\text{H}}^2}^{1/2}
\]

A finite impulse response filter (FIR) is designed to implement the Hilbert transform (HT). The HT-FIR filter can be realized in analog or digital forms. In this paper, the digital form of HT-FIR filter is adopted. This filter minimizes the maximum error between the desired frequency response and the actual frequency response. Fig. 1 represents the block diagram representation of the envelope detector using Hilbert transform.

The envelope of the normal sinusoidal signal is constant, whereas for disturbance signals, the shape of the envelope varies.

The envelope of voltage sag and flicker are shown in Figs. 2 and 3, respectively, along with the original signal. The envelope of voltage flicker signal resembles an amplitude modulated (AM) signal with the nominal frequency of 50Hz [15].

![Fig. 1. Block diagram of the envelope detector using Hilbert Transform.](image-url)
The envelope of the flicker signal is a sinusoidal wave. Thus the shape of the envelope clearly distinguishes the type of the power quality disturbance.

From the coefficients of HT, the following statistical informations are calculated:

Mean, \( F_1 = 1/M \sum x_A[k] \)  

Standard deviation, \( F_2 = 1/N \sum_k (x_A[k] - 1/N \sum x_A[k])^2 \)  

Peak value, \( F_3 = \max(|x_A[k]|) \)  

Energy, \( F_4 = \text{norm}(|x_A[k]|)^2 \)  

These quantities are used as input features of the neural network.

4. Radial basis function neural networks

Radial basis function network [9] is a class of single hidden layer feedforward neural network. The architecture of RBF neural network is shown in Fig. 4. The network has an input layer, a hidden layer and an output layer. The transfer functions in the hidden layer nodes are similar to the multivariate Gaussian density function

\[ \phi_j(x) = \exp\left(-\frac{|x-\mu_j|^2}{2\sigma_j^2}\right) \]  

where \( x \) is the input vector, \( \mu_j \) and \( \sigma_j \) are the center and spread of the corresponding Gaussian function. Each RBF unit has a significant activation over a specific region determined by \( \mu_j \) and \( \sigma_j \). Thus each RBF represents a unique local neighborhood in the input space. The connections in the second layer are weighted and the output nodes are linear summation units. The value of kth output node \( y_k \) is given by

\[ y_k(x) = \sum_{j=1}^{b} w_{kj} \phi_j(x) + w_{k0} \]  

where \( w_{kj} \) is the connection weight between the kth output and the jth hidden node and \( w_{k0} \) is the basis term.

The training of RBF is done in three sequential stages [11]. The first stage of the learning consists of determining the unit centers \( \mu_j \) by the k-means clustering algorithm [10]. Next, the unit widths

![Fig. 2. Voltage swell and its envelope.](image1)

![Fig. 3. Flicker and its envelope using Hilbert Transform.](image2)

![Fig. 4. Architecture of RBF neural network.](image3)

![Fig. 5. Test system for generating power quality disturbances.](image4)

Table 1

<table>
<thead>
<tr>
<th>Transform type/ANN type</th>
<th>RBF (%)</th>
<th>BPNN (%)</th>
<th>Fuzzy ARTMAPS (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hilbert transform</td>
<td>97</td>
<td>94</td>
<td>88</td>
</tr>
<tr>
<td>S-transform</td>
<td>85</td>
<td>81.6</td>
<td>78</td>
</tr>
<tr>
<td>Wavelet transform</td>
<td>79</td>
<td>70</td>
<td>68.6</td>
</tr>
</tbody>
</table>
$\sigma_j$ are determined using a heuristic approach that ensures the smoothness and the continuity of the fitted function. The width of any hidden node is taken as the maximum Euclidean distance between the identified centers. Finally, the weights of the second layer connections are determined by linear regression using a least squares objective function.

RBF networks can be viewed as alternative tool for learning in neural networks. While, RBF networks exhibit the same properties as back propagation networks such as generalization ability and robustness, they also have the additional advantage of fast learning and ability to detect outliers during estimation [13].

5. Simulation results

This section presents the details of the ANN-based model developed for disturbance waveform classification. The sample power system shown in Fig. 5 was used to generate the data required to develop the neural network.

The system was simulated in Matlab/Simulink and the various power quality events such as sag, swell, transients, harmonics and voltage fluctuation along with normal signal were generated by creating various faults and through harmonic injection. Faults were created at different locations in an attempt to collect samples from different locations. Totally, 3000 samples were generated with 500 samples from each category. The signals were sampled at 256 points/cycle and the normal frequency is 50 Hz. Hilbert transform was applied to the generated signals and from the coefficients of HT, energy, standard deviation, mean and variance are calculated. These four quantities are the input features of the RBF network.

**Case 1:** Performance of Hilbert transform without adding noise to the disturbance signals:

The RBF was trained using the hybrid algorithm explained in the previous section. After training, the network was tested with the test data. The recognition rate during the testing stage is given in the second column of Table 1.

For comparison, wavelet transform and S-transform were applied to extract the features and the extracted features are used to train the back propagation network and fuzzy ARTMAP. In wavelet transform based approach, the signal is decomposed into 8 levels. The feature vector size is $32 \times 4$, where 8 represents 8
levels. In S-transform sassed approach, energy, mean, standard deviation and peak value are taken as the features. The recognition rate in each case is also given in Table 1.

The RBF classifier shows better classification performance than the other classifiers. The classification of the Hilbert transform based RBF network is 97%. Figs. 6–8 displays the results obtained using different feature extraction techniques and by using RBF, BPNN and fuzzy ARTMAP classifiers.

The x-axis of each graph represent classes (i.e. 1-normal, 2-sag, 3-swell, 4-transient, 5-flicker and 6-Harmonics). The y-axis gives information about the percentage of classification achieved using each combination. From Fig. 6, it is observed that class 1(normal), class 3 (swell) and class 5 (transient) are perfectly classified with the classification accuracy of 100%, whereas the accuracy for the remaining classes is 96%. Similarly, the classification rates for other ANNs with different feature extraction are shown in Figs. 7 and 8. From the above graphs, it is observed that the RFF classifier with Hilbert transform based feature extraction provides the highest percentage of classification accuracy.

Case 2: Performance under noisy environment

Table 2
Classification results using ANN (after adding noise).

<table>
<thead>
<tr>
<th>Transform type/ANN type</th>
<th>RBF (%)</th>
<th>BPNN (%)</th>
<th>Fuzzy ARTMAPS (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hilbert transform</td>
<td>94</td>
<td>90</td>
<td>83</td>
</tr>
<tr>
<td>S-transform</td>
<td>80</td>
<td>77</td>
<td>73</td>
</tr>
<tr>
<td>Wavelet transform</td>
<td>76</td>
<td>72</td>
<td>66.6</td>
</tr>
</tbody>
</table>

Fig. 10. Wavelet Transform of the sag signal added with noise.

Fig. 11. Results of Hilbert transform based ANN classifier.
In this case, the generated signals are added with 30db Gaussian noise. A sample noise added voltage sag signal and the envelope detected by Hilbert transform are shown in Fig. 9. Fig. 10 shows the wavelet transform of the voltage sag signal.

From Figs. 9 and 10, it is evident that the Hilbert transform has the ability to detect the presence of disturbances even under noisy environment whereas, the wavelet transform does not possess that capability.

Noise was added with all the 3000 samples and the features are obtained by applying statistical properties such as mean, variance, standard deviation and energy. These features are given as input to the radial basis function neural network. The classification results of RBF neural network along with the performance of other ANN architectures namely BPNN and fuzzy ARTMAPs in combination with S-transform and wavelet transform.

From Table 2, it is clear that, the Hilbert transform based envelope detection technique in association with RBF network produces best performance compared to other techniques.

Fig. 11 shows the percentage the correctly classified events obtained from Hilbert transform based envelope detection techniques using RBF, BPNN and fuzzy ARTMAPs.

It is observed from Fig. 11 that, using RBF classifier, the normal pure sine wave is perfectly classified, where as the remaining classes produce the classification accuracy ranging from 90% to 95% and the overall accuracy is 94%. The RBF classifier produces the highest percentage of accuracy in the noisy environment than the other ANN architectures.

6. Conclusion

In this paper, an attempt has been made to extract efficient features of the power quality disturbances using Hilbert transform and to classify the disturbance signal using RBF neural networks. The features extracted from the Hilbert transform are very simple and yet very effective. The RBF network takes less time for training and the classification accuracy is very high. Compared to the wavelet transform and S-transform, the Hilbert transform can be quickly calculated, so that the proposed method is efficient. Moreover, this method shows low sensitivity to noise levels and produces better classification accuracy even under the noisy environment.

References


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