

Discriminant Analysis and Hilbert Huang Based Power Quality Assessment

Stuti Shukla Datta, Namrata Dhanda

Abstract: This work deals with Hilbert Huang transform and discriminant analysis based assessment of power signals. Hilbert Huang transform is a combination of Empirical mode decomposition (EMD) and Hilbert Transform. EMD is a data assisted processing technique that works on the time scale difference between local extremas (maxima and minima points of a signal). Unlike Fourier Transform, Wavelet Transform and Stockwell Transform, EMD does not employ any basis function or a window function and highly depends on the data of the signal. Power system is a highly vulnerable system subjected to several technical constraints and hence deviation of power signals from their normal level is inevitable. Thus, in order to study the reasons that cause the deviation of normal values, signal processing technique based on EMD is applied to power signals which are obtained by simulating various power scenarios in MATLAB Simulink platform. Decomposed components are then transformed in the frequency domain using Hilbert Transform. Hilbert transform helps in the extraction of features of the signal in consideration. These features are then subjected to discriminant analysis based classifier to identify the class of the raw input. Efficiency of the methodology is evaluated and results obtained are highly promising.

Keywords: Discriminant Analysis, Empirical Mode Decomposition, Hilbert Transform, Power Signals, Signal Processing

I. INTRODUCTION

Power Quality problems such as voltage sag, swell, spike harmonic distortions etc. severely affect the reliability of the power system. Power anomalies may result in machine failures, relay malfunction, instabilities, interruptions etc. An outage or a surge may hamper the production for hours resulting in heavy monetary loss in the business. Thus maintaining certain standards as far as power quality is concerned is imperative both for consumers and utilities. Penalty imposition as a consequence of deteriorating the power quality could make them cautious against the distortion level produced due to their own usage. Power Quality evaluation is also needed when planning a new industrial installation at particular site. The information on the type of the disturbances, its duration and frequency of occurrence are needed beforehand so that mitigation action could be incorporated in the equipment itself thereby avoiding any losses due to power quality disturbances. Moreover, integration of the renewable energy sources and plug in

vehicles to the system further adds to the power quality problem. Thus power quality monitoring and analysis is an essential task. In this aspect number of methods is reported in the literature for identifying the class of the disturbance [1-10]. Authors in [5] have successfully employed Hilbert Huang Transform for feature formulation and modified version of the algorithm in [11] for the identification of disturbances under noisy environment. However the identification not only relies on the features but also on the classifier. Thus in this paper authors investigate the efficiency of discriminant analysis as a classifier in identifying the power quality events. The features are formulated using HHT.

This paper is organized into six sections. Section I deals with introduction parts and discuss the need for identifying the disturbance class. Section II gives a description of Hilbert Huang Transform. Section III explains the principle behind Discriminant analysis based classifier. Section IV deals with feature extraction using Hilbert transform and identification of events using discriminant analysis. Section V deals with results and Section VI gives the conclusion of the work.

II. HILBERT TRANSFORM AND EMPIRICAL MODE

In order to obtain instantaneous frequency or phase information, it is imperative to have an imaginary part of the real valued signal and Hilbert transform helps in the computation of these imaginary parts. However, the Hilbert transform of a distorted signal has no meaning [13] unless it is decomposed into its oscillating components which are monotonic in nature or have a very narrow band of frequencies. EMD based approach which is discussed next helps in obtaining these components from signals. Once these components are extracted, Hilbert transform is applied and frequency and phase information is obtained. The conventional Hilbert transform of a continuous signal $Y(t)$ is given by the expression as:

$$\hat{Y}(t) = \int_{-\infty}^{\infty} \frac{Y(\tau)}{t - \tau} d(\tau) \quad (1)$$

The continuous Hilbert transform results in 90 degree radian phase shift in the frequency domain so transfer function can be well written as:

$$HH'_1(\omega) = \begin{cases} i & \omega > 0 \\ 0 & \omega = 0 \\ -i & \omega < 0 \end{cases} \quad (2)$$

In the discrete domain transfer function can be written as:

$$HH'_1(\omega) = \begin{cases} i & 0 < \omega < \pi \\ 0 & \omega = 0 \text{ \& } \omega = \pi \\ -i & -\pi < \omega < 0 \end{cases} \quad (3)$$

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An explanation on the transform can be referred from [12]. Thus Hilbert transform of signal $YY(t)$ results in an analytical signal $ZZ(t)$ as:

$$ZZ(t) = Y(t) + \hat{Y}(t) = A(t)e^{-i\theta(t)} \quad (4)$$

where

$$A(t) = \sqrt{[Y(t)^2 + \hat{Y}(t)^2]} \quad (5)$$

$$\text{and } \theta(t) = \tan^{-1} \frac{\hat{Y}(t)}{Y(t)} \quad (6)$$

In the frequency domain Hilbert transform works as a 90 degree phase shifter and in the time domain it gives the convolution of the extracted mode with $1/t$ thereby emphasizing the local features of a signal. The Hilbert Transform of a monotone signal, that satisfy the condition of local symmetry w.r.t. zero mean, can give information about instantaneous frequencies (which is given by $\omega = d\theta/dt$). Fig.1 (a) depicts a waveform having two frequency components present at different time and its frequency information obtained from Hilbert Transform shown in Fig. 1(b).

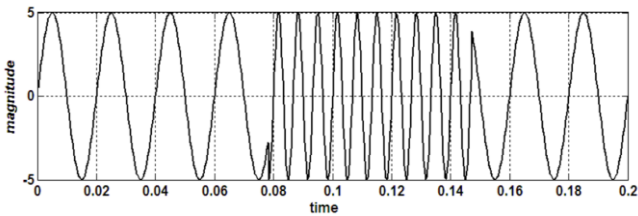


Fig. 1(a) Waveform with frequency components at different times

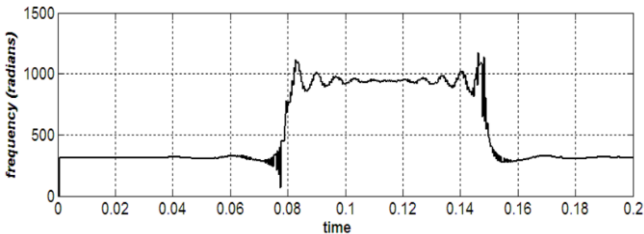


Fig. 1(b) Frequency spectrum of the signal in (a) using Hilbert Transform

III. EMPIRICAL MODE DECOMPOSITION

The shape of a signal is dependent on the oscillating components present in it. Separation or extraction of these components from signal can be achieved through empirical approach adopted in EMD algorithm. This empirical approach proceeds with identifying the local extreme points (the maximas and the minimas) on the first stage followed by generation of envelopes (upper and lower) which are developed by combining the identified extremas. An average of the two envelopes give an estimate of the first oscillating mode present in the signal. This mode is separated from original waveform and termed as intrinsic mode function if it satisfies the following two conditions:

1. Difference between number of extrema points and number of zero crossings must be zero or differ at most by one.
2. The mean value of the upper envelop and lower envelop should be zero.

Now, if these conditions are satisfied, the mode extracted fulfills the criteria to be called as an intrinsic mode. This mode is then separated from the original waveform. The remaining signal is again subjected to process of identifying extrema,

generating upper and lower envelopes and checking above mentioned conditions in order to identify the next oscillating mode. Thus a waveform shape is a result of superposition of multiple frequency components and can be extracted using EMD. The technique is well described in [12]. A signal with one frequency component has just one mode of oscillation and satisfies the condition of intrinsic mode. In Fig. 2 different oscillating components are extracted using EMD[5].

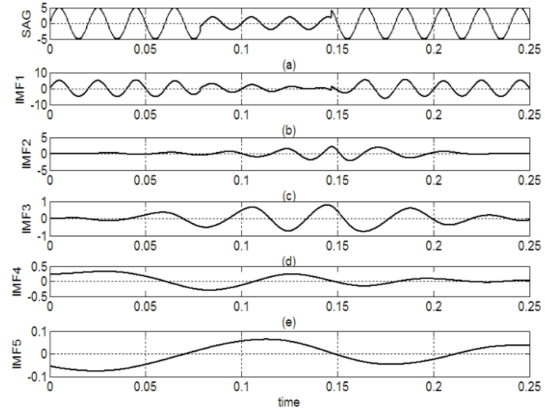


Fig. 2 (a) Voltage Sag (b)-(f) Intrinsic mode functions of the voltage sag

IV. DISCRIMINANT ANALYSIS

Discriminant analysis is basically a statistical tool that is used to evaluate the acceptability of a classification algorithm, given a group membership function or in other words it is used for assigning an object to a particular group when we have a number of groups at our discretion. In order to perform discriminant analysis, it is necessary to know some group assignments in advance. Discriminant analysis is a classification technique that is based on the calculation of the statistical distance of the raw input data and the class centers of the objects under consideration[14]. The value of the statistical distance accounts for the location size and the shape of the class clouds. This distance is also called as the Mahalanobis distance. It is further assumed that whenever the data follows a Gaussian distribution, the statistical distance makes use of a covariance matrix to estimate the distance between new object and the estimated centroid of the class. For ease of understanding, we illustrate the concept of LDA and apply LDA operations to a two-class problem. The following are the steps involved in performing LDA:

- i. In the first set we form data sets and the test sets, which are meant to be classified in the original space. We can think of data sets being represented in the form of matrix which consist of features of the objects in the data set as shown below:

$$\begin{array}{cc}
 a_{11} & a_{12} & \beta_{11} & \beta_{12} \\
 a_{21} & a_{22} & \beta_{21} & \beta_{22} \\
 \text{set1} = & \dots\dots\dots & \text{set2} = & \dots\dots\dots \\
 & \dots\dots\dots & & \dots\dots\dots \\
 a_{m1} & a_{m2} & \beta_{m1} & \beta_{m2}
 \end{array}$$

ii. In the next step we calculate the mean of each data set and the mean of the entire data set.

$$\eta_3 = p_1 \times \eta_1 + p_2 \times \eta_2 \quad (7)$$

where p_1 and p_2 are the a priori probabilities of the classes. If we consider the case of simple two class problem, we usually take the probability factor to be 0.5.

iii. In order to determine a criterion for class separability in LDA, we use the concept of within-class and between-class scatter. The expected covariance of each of the class is called as the within-class scatter. The calculation of scatter measures can be calculated using Equations 3 and 4.

$$S_w = \sum_i p_i \times \text{covariance}_j \quad (8)$$

Therefore, for the two-class problem,

$$S_w = 0.5 \times \text{covariance}_1 + 0.5 \times \text{covariance}_2 \quad (9)$$

All the covariance matrices possess the property of being symmetric. Let covariance_1 and covariance_2 be the covariance of set1 and set2 respectively. Then we can calculate the covariance matrix computed using the following equation.

$$\text{covariance}_j = (x_j - \eta_j)(x_j - \eta_j)^T \quad (10)$$

The between-class scatter is computed using the following equation:

$$S_b = (\eta_1 - \eta_3)(\eta_1 - \eta_3)^T \quad (11)$$

We can consider S_b of as the covariance of data set whose members are the mean vectors of each class. As defined earlier, the optimizing criterion in LDA is the ratio of between class scatter to the within-class scatter.

iv. An Eigen vector of a transformation is represented by a 1-D invariant subspace of the vector space in which the transformation is applied. A set of linearly independent eigenvectors is one whose corresponding eigen values are all non-zero and they are invariant under the transformation. We can represent a vector space as a linear combination of eigen vectors. An eigen value of zero depicts a linear dependency among the features. In order to get a non-redundant feature set we consider all vectors corresponding to which eigen value is non-zero whereas the ones having a zero value for eigen vector are neglected. In LDA, the transformations are computed as the eigen vector matrix defined in Equations 13 and 14 below:

$$\text{criterion}_j = \text{inv}(\text{covariance}_j) \times S_b \quad (12)$$

For the class independent transform, the optimizing criterion is computed as:

$$\text{criterion}_j = \text{inverse}(S_w) \times S_b \quad (13)$$

v. After obtaining the transformation matrices, we transform the data sets by using either the single LDA transform or the class specific transforms. Transforming the entire data set to one axis provides definite boundaries for the classification of data. The decision region in the transformed space is a solid line separating the transformed data sets thus for the class dependent LDA,

$$\text{transformedset}_j = \text{transform}_j^T \times \text{set}_j \quad (14)$$

For the class independent LDA,

$$\text{transformed_set} = \text{transform_spec}^T \times \text{data_set}^T \quad (15)$$

In the same manner we can classify the test vectors using the

Euclidean distance of the test vectors. Similarly the test vectors are transformed and are classified using the Euclidean distance of the test vectors from each class mean.

vi. After completing the transformations using LDA transforms or Euclidean distance, we classify the data points. Euclidean distance is calculated using Equation 17 where the mean of the transformed data set, is the class index and is said to be the test vector. Thus for classes, Euclidean distances are obtained for each test point.

$$\text{dist}_n = (\text{transform.n.spec})^T X \mathbf{x} - \eta_{n\text{trans}} \quad (16)$$

V. FEATURE EXTRACTION AND IDENTIFICATION OF POWER QUALITY EVENTS

The process employed for feature extraction is explained step wise for the convenience of the reader:

Using EMD extract the oscillating modes of the waveform.

After decomposition first two intrinsic modes are subjected to Hilbert Transform

From the analytical signal obtained from Hilbert Transform of first two IMFs following feature are extracted.

Energy component of the first IMF

Component of the second IMF.

Standard deviation of the phase contour of first IMF

Standard deviation of the magnitude contour of first IMF

Identification of the event is performed through K means method. Identification process is explained step wise:

1. We are considering three power quality events namely CC1=sag; CC2=swell; CC3 harmonic; CC4=transient
2. For each of these events 80 waveforms or datasets are generated. That means 320 datasets in all.
3. For each of 80 data sets corresponding to an event we obtain features.
4. We employ 60 datasets for evaluating the centroid of the features.
5. Similarly for each different event centroid of their feature vector is evaluated.
6. Here 20 datasets of each event are kept for testing and obtaining the efficiency of identification of K means method.
7. For any new feature for which the class is to be identified four statistical distances are evaluated and nearest distance identify the class of the new event.

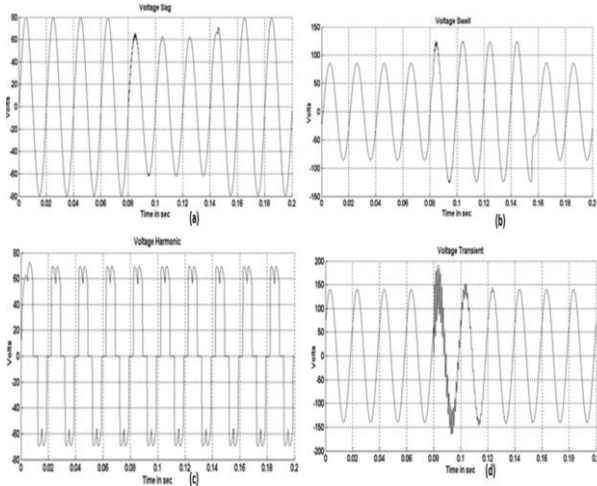


Fig.3 Various power quality event considered in the paper (a) Voltage sag (b) Voltage well (c) Harmonics (d) Transients

VI. RESULTS AND DISCUSSIONS

Table I depicts the classification efficiency of discriminant analysis and Hilbert Huang based classification methodology. It is seen that 20 cases of each events are tested and it is found that all classes except the Class C4 is 100 percent identified. Though classification efficiency for the class C4 is 95% . The overall efficiency for the algorithm is 98.75%.

Table I

CLASSES	CC1	CC2	CC3	CC4
CC1	20			
CC2		20		
CC3			20	
CC4			1	19
%Classification efficiency	100	100	100	95
%Classification Error	0	0	0	5
Total Efficiency of the Classifier	98.75%			

With Empirical Mode Decomposition different oscillating modes of a signal are extracted. These modes are associated with different intrinsic time scales. Transformation of these IMF in the frequency domains using Hilbert Transform can give a better time frequency distribution for non-stationary signals.

VI. CONCLUSION

In this work Hilbert Huang along with discriminant analysis is employed for identifying the four power quality events. Empirical Mode Decomposition does not employ any basis function and decomposition process depends only upon the local extremas (maximas and minimas). After extracting the inherent modes of waveform Hilbert transform is of these oscillating signals are obtained. From the transformed domains four features are extracted. These features are then subjected to discriminant classifier. The discriminant classifier calculates the statistical distance between the

centroid of all the event class to the new input whose class is to be identified. The efficiency of the classifier is evaluated and results obtained are encouraging.

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