Event Signal Characterization for Disturbance Interpretation in Power Grid

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***Abstract*—This paper presents the signal processing approach to detect and characterize the physical events that occur in power system using PMUs signals. A small window is applied so that the extracted spectral features belong to a stationary signal. This is based on applying empirical mode decomposition, followed by square root of spectral kurtosis (SRSK) for computation of statistical indices to indicate the event occurrence. Subsequently, features from these events are extracted using mel frequency cepstral coefficients on SRSK.**

***Index Terms*—Event detection, PMU, Power grid, Monitoring, Spectral Kurtosis, Wavelet, Characterization**

I. Introduction

WIDE area monitoring is a first step in the evolution of conventional grid into "smart grid". The smart grid will be made more intelligent, with much more sensing and embedded control action in loop. The embedded intelligence will however make the grid even more complex, creating the need for continually improved tools to help designers/ operators to design and operate the smart grid of tomorrow need. The tools therefore require establishment of appropriate decision criteria by which events can be distinguished.

The grid operation at normal conditions can be thought of as slow changing power flow due to variation in the load, and on manual or automatic changes to the real output power of generators. However, the grid regularly faces threat due to disturbances like generator failure or line trip. Also, the reliable operation of grid is constrained, to be able to operate without any violations under above contingencies.

Since past one decade, it is well established that the PMUs finds application in power system monitoring and control in a wide area network (WAN) due to high speed sample rate (30 or 60 samples per second) [1] as compared to the supervisory control and data acquisition (SCADA). To be specific, several researchers have reported monitoring methods to determine system stability from PMUs data. These investigations are based on voltage phase angle across a cutest of lines [2], statistical means for fast-slow and critical slowing down [3], monitor of rotor angle dynamics using Lyapunov exponent [4], with recent advances described in [5] & [6].

Now, independent system operators enforce power flow limits on important connections in order to ensure stable operation at the time of severe event/disturbances or contingency in the network [7]. Such events are intuitively determined by the system operators, relying on experience. The power system disturbances arising due to various reasons, have statistical characteristics, mostly in non-linear and non-stationary nature, thus, the PMUs data analysis in the time and
frequency domains plays an important role in the development of event diagnosis scheme.

Due to the non-stationary of PMU signals, obtained at the time of disturbances, traditional analytic tools have limitations when discovering useful features. In recent years, wavelet transform have been proposed as it provides a more flexible time-frequency resolution. The performance of neural network however depends on the features used in the classification. Despite several techniques proposed in the past, robust power system event diagnosis is still an open problem due to the poor frequency resolution in the low-frequency region, poor features used and the non-stationary nature of underlying signals. Very little work has been carried out in the lines of developing scientific procedures for analysing different events. The research study can be performed to analyze events due to overloads, voltage deviations, loss of line and operator action.

The method of auditory features extraction based on the Mel frequency cepstrum coefficient (MFCC) has been successfully applied in auditory recognition and reported widely [8]. This is due to fact that said technique is capable to handle the dynamic features as they extract both linear and non-linear properties of the signal [9]. The method of feature extraction using MFCC can be similarly adopted for power system events characterization from PMUs signals, as it contains both linear and nonlinear features. Computing the cepstrum directly from PMUs signals using a single time-resolution is probably suboptimal in the sense that it cannot distinguish between these different events.

Thus, the approach can adopt to first decompose the PMUs signals into monotonic components using empirical mode decomposition (EMD) technique. For non-stationary signals, the technique results in a different scale in the time domain that can offer better frequency resolution in the low frequency region. And subsequently incorporating time-domain information into discriminating features using derivatives of the MFCCs can provide better features for event diagnosis.

In this paper, we propose a systematic approach to characterize the events that takes place in the system. The novelty of the study is that the system operator at remote central level can be alarmed about the type of event occurrence. Thus, the potential risk if any, can be known in advance, guiding the operator to take suitable action.

This paper is organized as follows. The signal processing techniques adopted in algorithm is described in Section II, followed by proposed event detection scheme in Section III.

The description on case studies on PMU data is detailed in Section IV. In the next Section V, the results are discussed on the performance of proposed scheme and finally, the conclusions are drawn in Section VI.

II. Signal Processing Techniques

This section presents the signal processing techniques that are applied for detection of events and quantify the dynamics of signals, following the disturbances.

A. Empirical mode decomposition (EMD):

The EMD first introduced by Huang et al. [10] is capable to adaptively decompose any signal into a set of L_I level of complex-valued oscillating components, known as intrinsic mode functions (IMF) and a residual representing the trend. These IMF define phase information for the real and imaginary components locally. Mathematically, the set of IMF, $\{I_l(t)\}_{l=1}^{L}$ and a residual value is expressed as:

$$S(t) = \sum_{l=1}^{L} I_l(t) + r(t) \tag{1}$$

The IMF extraction from the data segment is based on an iterative method known as shifting algorithm and it can found in [11].

B. Spectral Kurtosis:

The spectral kurtosis (SK) is a spectral descriptor that overcomes the inefficiency of power spectral density for detection and characterization of transients in a signal [12]. In simple terms, spectral kurtosis (SK) is defined as the normalised fourth-order moment of the real part of the STFT [13]. The SK is an extension of statistical measure of kurtosis defining the impulsivity of the event present in the signal in the frequency domain. The details on this technique and its combination with EMD for event detection is described in [14].

C. Mel Frequency Cepstral Coefficients (MFCC):

Mel Frequency Cepstrum (MFC) is a representation of linear cosine transform of a short-term log power spectrum of speech signal on a non-linear Mel scale of frequency. Cepstrum is obtained by taking the inverse transform of the logarithm of Fourier transform of the signal.

The MFCC are derived from mel frequency cepstrum which can find its application for representing high frequency event associated signals. The MFCC processing can be performed in following three steps:

- Conversion of time-domain signal into frequency domain using the fast Fourier transform.
- Mapping of power spectrum into mel scale, using triangular overlapping windowing. Such filters use mel scale.
- Obtain log of the outputs and discrete cosine transform (DCT) of the list of mel log powers. The amplitudes of resulting spectrum gives the mel-frequency cepstral coefficients (MFCCs).

D. Extraction of Features

A small size windowing often referred as frame is passed through hamming window function to avoid discontinuities, after which discrete Fourier transform is applied on each framed size.

First-order differential (Delta) Mel frequency ceptrum coefficients ($\Delta MFCC$) are calculated as:

$$D(n) = \frac{1}{\sqrt{\sum_{i=-p}^{p} i^2}} \sum_{i=-p}^{p} \mathbb{C}(n+i) \tag{2}$$

Where, $D(n)$ is the n frame of $\Delta MFCC$, $\mathbb{C}(n)$ is the n frame of Mel frequency ceptrum coefficients, and p is a constant taken as 2 [9]. Similarly, second-order differential (Delta-Delta) Mel frequency ceptrum coefficients ($\Delta\Delta MFCC$) are calculated as:

$$D'(n) = \frac{1}{\sqrt{\sum_{i=-q}^{q} i^2}} \sum_{i=-q}^{q} i . D(n+i) \tag{3}$$

These features describe how the MFCCs change between subsequent frames of data, and can be likened to frame-rate spectral flux.

Each type of event occurrence in the signal can be transformed into a sequence of feature vectors, each vector representing the signal in a small time window. This feature extraction step reduces the dimension of input signals into lower dimensional vectors.

III. Event Analysis Scheme

It is expected in future, that the operators will be issued alert message through real-time detection of abnormal events that often occur in power system. For online visualization tool, the PMUs data sampled at a given rate allow direct observation of power system dynamics. On particular event detection, the next step is to extract event related characteristics and classify them so as to quickly provide actionable information for decision making.

A. Segment Processing

Consider a large scale PMU N_P deployment in wide-spread power grid network, each providing p measurement of signals. Typically, a PMU measures $p = 5$ time series bus data; frequency (F_r), active power (P), reactive power (Q), voltage angle (A_g) and voltage magnitude (V). A total of $Z = N_P \times p$ measurements are thus collected at every time instant. The architecture for event detection in PMU data, characterization and classification is depicted in Fig. 1. As illustrated in Fig.1(a), the PMU data is segmented into fixed-length window of m samples being available at a rate of 50 or 60 Hz. Each segment $S = [\vartheta_1\ \vartheta_2 \ldots \vartheta_m]$ is a sequence of samples ϑ_i. Once the length of initial data segment equals to selected size of samples, the detection algorithm is initiated and updated after every m samples. The event detection algorithms based on computation of IMFs is applied on each segment. The algorithm determines if the new data segment in analysis has characteristics different from the previous/post segment to indicate an event. In other words, an assessment is made to check if post-event (normal) dynamics has reached steady state condition. It is emphasized to discriminate between normal and event conditions.

B. Computation of Event Detection Indices

The implementation of detection algorithms using EMD are shown in Fig. 1(b). The IMF of levels L are extracted for each segment. In the proposed scheme, SRSK obtained on first ($l = 1$) and last ($L - 1$) is referred as first-SRSK (FSK) and last-SRSK (LSK) respectively. The detection scheme is applied to calculate the detection statistical indices. The computed statistical signatures on the analysis segment are compared with those obtained on previous/post segment over the complete data length. Considering decomposition of segment into L level IMF, the total energy content at first and last IMF level can be determined from

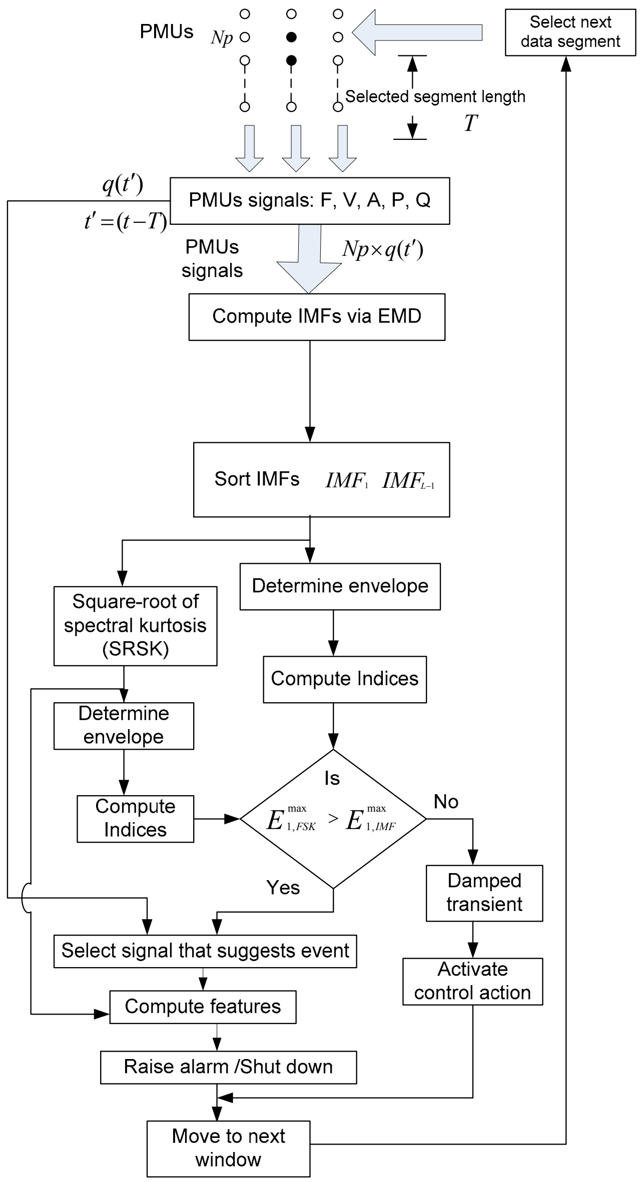
$$E_1(m; l = 1) = |I_1(m)|^2 \tag{4}$$

$$E_{L-1}(m; l = L - 1) = |I_{L-1}(m)|^2 \tag{5}$$

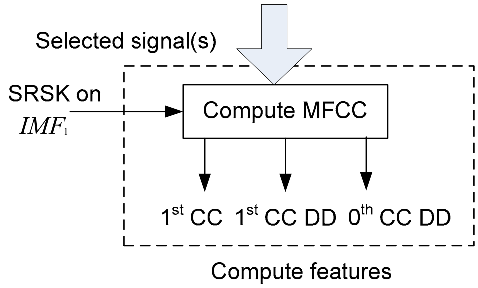
Maximum energy is given as

$$E_1^{max} = Max\{E_1(m; l = 1)\},$$
$$E_{L-1}^{max} = Max\{E_{L-1}(m; l = 1)\} \qquad (6)$$

The maximum energy computed from FSK, $E_{1,FSK}^{max}$ is compared those obtained from corresponding level IMF, $E_{1,IMF}^{max}$. This detection index can be useful in quantifying the event associated signal characteristic. For example, as expected, the total energy content or maximum energy corresponding to high frequency component, i.e first IMF is an indication of transient event type, for e.g. a short circuit, line trip or similar event. On other hand, those indices obtained at last IMF can be used to signify slow change or even critically damped modes in frequency signal. For each event detected in the different signals (F_r, P, Q, A_g or V) during the execution of algorithm, the signal that captures the strongest disturbance is subsequently characterized (Fig.1(a)).



(a) Event diagnosis scheme



(b) Event characterization step

Figure 1. Proposed event detection and characterization flowchart

C. Computation of Indices and Features

Feature extraction from the signals corresponding to the events in terms of spectral features is one of the approach for its characterization. The preliminary analysis on event characterization uses computation of skewness pearson coefficient defined as:

$$SPC_2 = \frac{(Mean - Median)}{Standard\ Deviation} \qquad (8)$$

The coefficient is positive or negative depending on whether the distribution is positively skewed or negatively skewed. This follows the detailed investigation using MFCC. The process of extracting MFCC features can be outlined as follows. With the availability of first ($l = 1$) IMF on the signal corresponding to event occurrence, the above described MFCCs are extracted in short time-scales as overlapping sliding windows in the form of frames. The spectrum changes very quickly due to non-stationary nature of signal, i.e. statistical properties vary with time. The MFCC contain both time and frequency information of the signal and thus makes more useful for feature extraction. Delta and Delta-Delta features are computed from signal (IMFs) frames, corresponding to zeroth cepstral coefficients (0^{th} CC) and first cepstral coefficients (1^{st} CC).

IV. PMUs Data Case Studies

A. PMU Signals

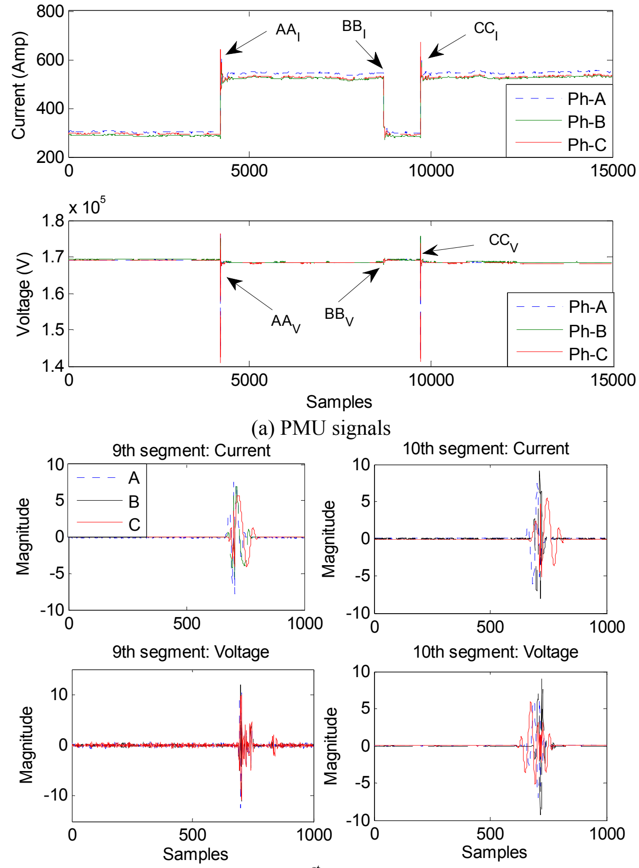
The PMU signals; three-phase current and voltage magnitude are sampled at 50 Hz and shown in Fig. 2(a). The PMU signals accompanied with events are indicated in said figure. The IMFs are obtained applying EMD technique on each segment consisting of 1000 samples for complete signal length. Fig. 2(b) shows the 1^{st} IMF level for current and voltage signals corresponding to 9^{th} & 10^{th} segment. The events can be observed in IMFs for voltage (AA_V, BB_V & CC_V) and current (AA_I, BB_I & CC_I) signals. It is indicated in Fig. 2(a) that the event corresponding to BB can be significantly observed in current signal with respect to voltage signal. Physically, the event occurrence is related current and do not have much impact on voltage signal. This is important to be distinguished using features.

V. Results and Discussion

This section presents the performance of above described event analysis schemes.

A. Event detection

Fig. 4 shows the computed maximum energy on first and last



(a) PMU signals

(b) 1st IMFs

Figure 2. Events and its analysis for PMU signals

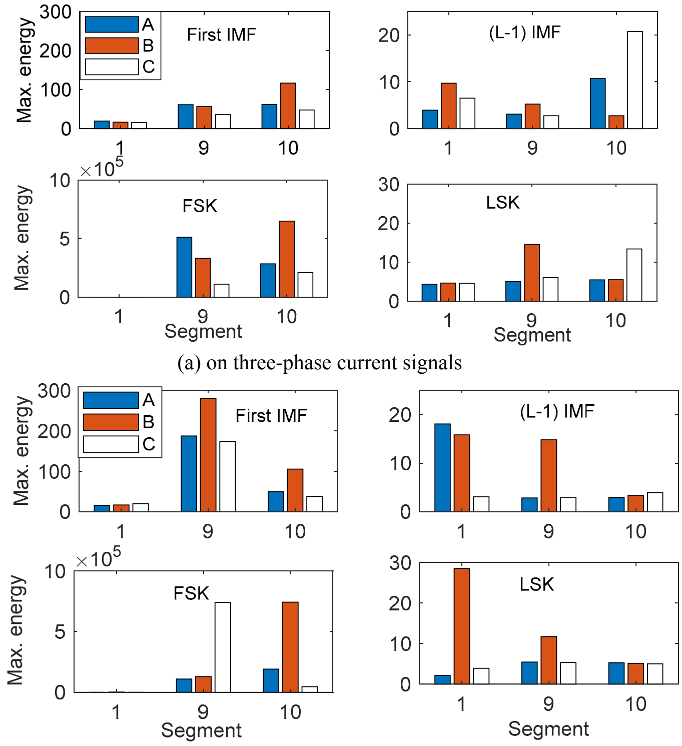
IMFs and those on SRSK of these IMFs, i.e. FSK and LSK. These indices have been shown for three phase signals; A, B, C of current and voltage in Fig. 4(a) and (b) respectively. It is clear that largest energy content is observable in first IMF level as compared to last level. As the events are of transient nature, due to peakiness property indicated by computation of SRSK, a many fold increased maximum energy can be seen on FSK. This is clearly observable for event induced segments 9 & 10 unlike segment 1, during which no-event has been indicated in raw signal (Fig. 2(a)). Thus, the event detection is convincing using the technique based on calculation of SRSK on first IMF. Further, least energy content is imperative on last IMF level or its LSK.

B. Event Characterization

The calculation of skewness pearson coefficient on PMUs signals Case I is shown in Fig. 5. It may be observed that for non-event segment, the coefficient calculated from first IMF and last IMF are opposite, i.e. negatively skewed, to corresponding to FSK and LSK. On other hand, for event segments; 9 & 10, the said coefficient on first IMF is positively skewed to FSK, while negatively skewed for last IMF with respect to LSK. This signifies whether the event is current or voltage change related to physical disturbance in the power system. Further, MFCC features are represented for segment 1 (non-event) and segments 9 & 10 (events). As indicated in Fig. 5(a), 1st CC for segment 1 lies within positive magnitude on y-axis. While those with events have zero mean and significantly increased magnitude.

Similarly, 0th CC Delta also suggests increased value for event occurrence segments, shown in Fig.5(b). But the intensity of event occurrence as reflected in voltage signal for segments 9 & 10 are not exactly similar.

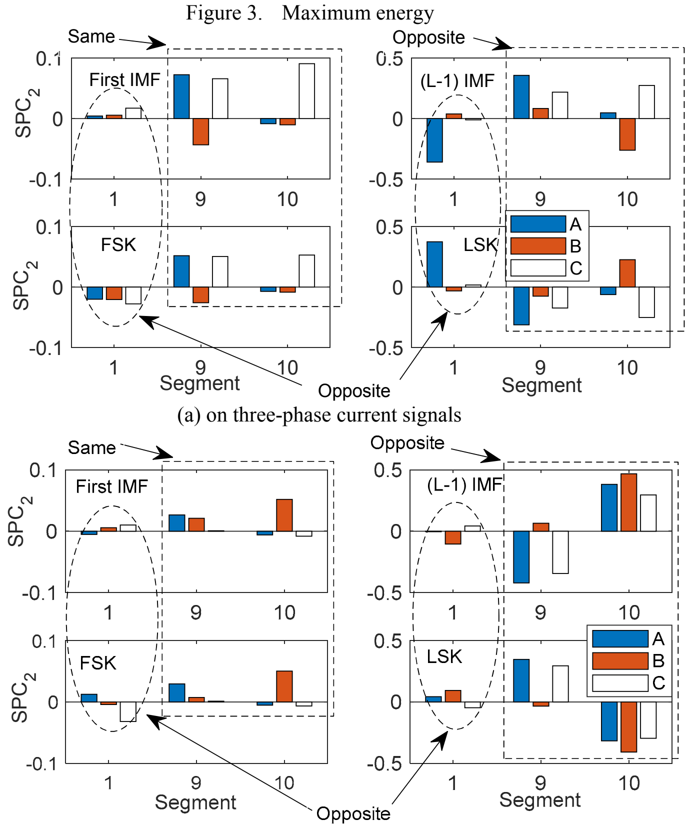
There is greater impact observed in segment 10 for voltage signal. The same affect is also indicated from 1st CC Delta as shown in Fig. 5(c).



(a) on three-phase current signals

(b) on three-phase voltage signals

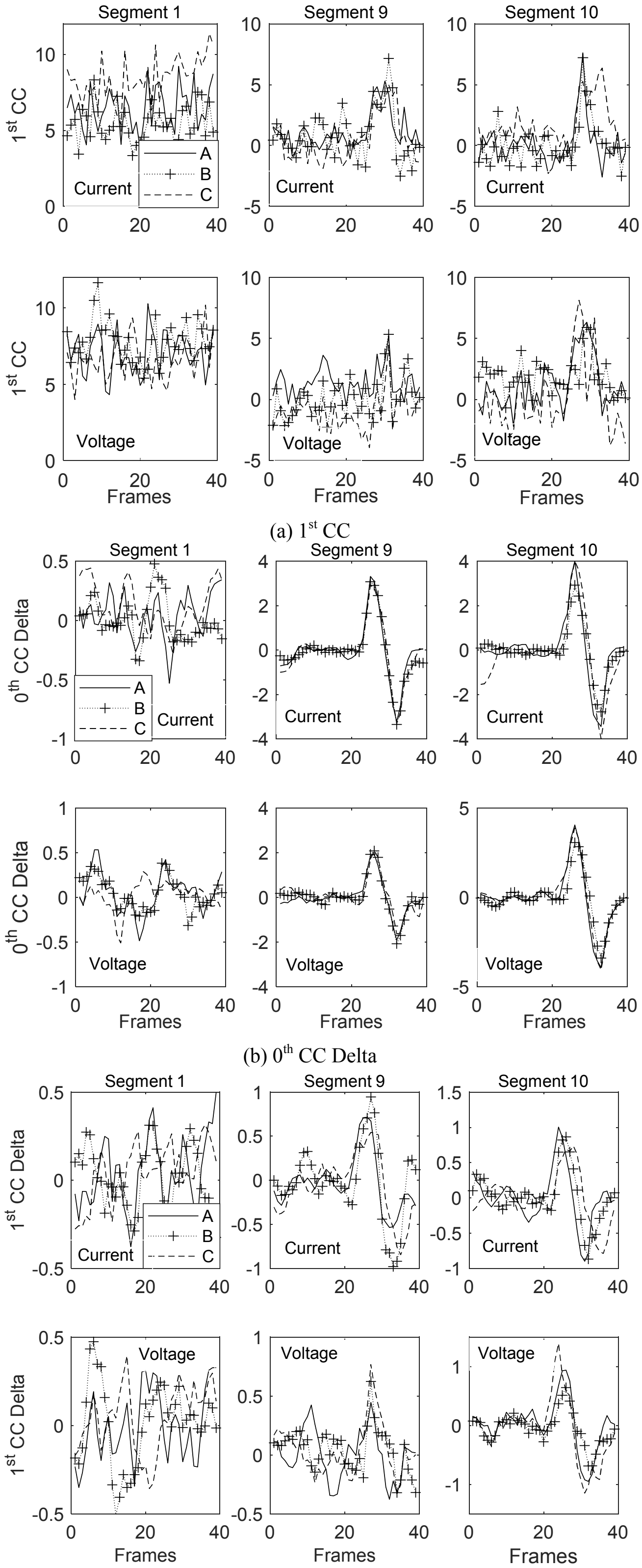
Figure 3. Maximum energy



(a) on three-phase current signals

(b) on three-phase voltage signals

Figure 4. Skewness pearson coefficient



(a) 1st CC

(b) 0th CC Delta

(c) 1st CC Delta

Figure 5. MFCC features

VI. Conclusions

The implementation of event detection and its characterization into physical disturbance was reported in study. The event detection step does not involve computation of threshold in normal conditions. The computation of SRSK on first IMF is more suitable for event detection than based on energy content analysis on corresponding to first IMF level.

It was possible to suggest the events as according to physical disturbance via analysing the corresponding MFCC features. However, further study is needed on slow varying disturbance type of events using MFCC features.

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