Automatic Segmentation Method for Voltage Sag Detection and Characterization

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***Abstract*—Although characterization of voltage sag is an essential part of voltage sag studies, the way that taking magnitude and duration as acknowledged basic characteristics cannot describe sag characteristics versus time. Hence automatic segmentation, which divides monitoring data sequence into segments, and characterization algorithm are proposed in this paper. The difficulty that how to divide segment automatically is overcome through two-stage segmentation algorithm based on singular value decomposition method. Then multi-dimension characteristics such as magnitude, duration, phase-angle jump, sag type and so on can be calculated. Hundreds of sag events data including measured in field and synthetic are utilized to validate the effectiveness and reliability of proposed method. Moreover, the detection and characterization algorithm are ported to installed monitors and backstage data center with C programming, timesaving and practical get validated.**

***Index Terms*—Automatic segmentation, detection method, multi-dimension characterization, transition segment, voltage sag monitoring.**

I. INTRODUCTION

Nowadays, voltage sag has been considered as one of the most important power quality problems by the power customers and utilities. The related data analysis is essential part for resolving sag problem with the wide using of power quality (PQ) monitors. And detection methods are required primarily where kinds of characteristics calculation of voltage sag play an important role.

There are several standards recommend measurement methods for monitoring PQ, such as IEC 61000-4-30, IEEE 1159-2009, and IEEE 1564-2014, where a single voltage magnitude value and a single duration value are acknowledged as basic characteristics of sag events [1]-[4]. In the last few decades, statistical characteristic is more concerned and voltage sag can be simplified described for quantifying and benchmarking. Utilities and customers utilize standard method as reproducible way of quantifying the performance of the supply at a specific location. However, from the point of view of effective data analysis, the two basic characteristics defined in these standards are insufficient for extracting information about underlying cause of voltage sag and the status of the power system. In addition, rather than magnitude and duration, new type electronic equipment may be sensitive to additional characteristics [5]-[8]. International working group JWG C4.110 sponsored by CIGRE/CIRED/UIE has presented a report about the research results aiming at improving the understanding of the compatibility between installations and the electricity supply [8]. The working group pointed out that the standard method of characterizing voltage sag leading to a significant loss of sag information. In order to enhance the sag analysis, it suggest dividing monitoring data sequence into several blocks, that is, segmentation method. Unfortunately, the working group does not virtually specify how to divide the recorded waveform into variable-size data blocks.

Segmentation is a preprocess that classifies monitoring data sequence into several data blocks according to statistic characteristics. Due to transition progress existing between two system states, it is the first step to locate boundaries of transition segment accurately. But there is still no acceptable method for automatic segmentation yet. Although visual inspection is often implemented for some other characteristics calculation [9-10], manual method mainly depends on human experience and is lack of practicability for automatic data processing and analysis. There are some methods dividing segments according to changes directly from the waveform or RMS sequence. Reference [11] utilizes first-order derivatives of fundamental voltage magnitude or RMS value to detect boundaries of segments. If the first-order derivatives exceed threshold, transition segment is detected, otherwise not. But the boundaries of transition segments are deeply influenced by threshold that is usually set empirically. There are also some sophisticated segmentation methods requiring high time resolution which exploits residuals of sinusoidal models to locate the transition segments. In [12], Kalman filtering is utilized to locate boundaries of transition segments. The drawback is that parameters of Kalman filter are sensitive to noise and the detection results are influenced by threshold too.

Dividing monitoring voltage sequence into segments is necessary reprocessing step before effective data analysis methods. To multi-dimension characterization sag events, an automatic segmentation method aiming at optimally choosing each segment is proposed. Detection algorithm improves the time resolution based on *dq* transform and mathematical morphology. Considering attribute of transition segment, singular value decomposition (SVD) method is utilized to find sudden change points of fundamental voltage magnitude sequence and the boundaries of transition segments can be located according to adaptive threshold. Then multi-dimension characteristics of each segment can be calculated. The effectiveness and reliability of proposed method has been validated by synthetic data and measured data in field. With better real-time performance and compute capability, the algorithm has been ported to installed power quality monitor and background center database.

II. SEGMENTATION AND MULTI-DIMENSION CHARACTERIZATION

A. *Adaptive segmentation approaches*

Segmentation is an important pre-processing step in many signal processing applications including medicine, physiological, astronomy, speech signal et al [13]-[16]. As shown in Fig.1, typical voltage sag recording waveform can be divided into distinctive parts, that is, pre-event, transition, during-event and post-event segment. In general, each one is relative stationary except for transition segment, which indicate the intermediate state between non-event and during-event. Therefore, voltage magnitude in transition segment always change abruptly from being three-phase balanced with nominal magnitude to being unbalanced with lower than nominal voltage. It is noted that the pattern with transition segments and during-event segments is not common with all sag events. Few cases that voltage changes continuously during the whole sag event are not considered in this paper.

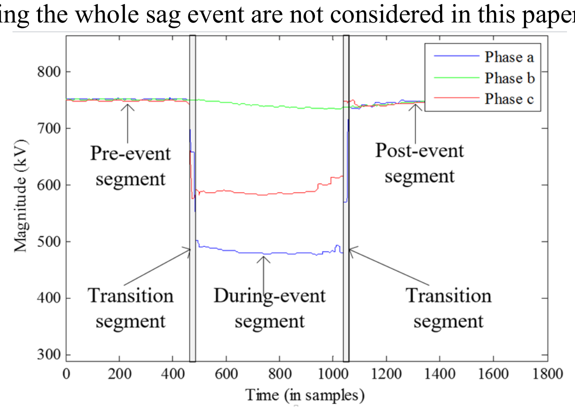

Figure 1. The standard voltage sag segmentation

It is known that non-event segment is associated with a duration of time within which the system does not change its state as well as transition segment indicates intermediate process between two system states. The preprocess of monitoring data reflects some information about fault initiating and protection operations, for instance, approximate time instant where the underlying system event is likely to have happened, which make segmentation more important.

B. *Multi-dimension characterizaiton*

Based on the segmentation which divides recording waveform into several parts with similar characteristics, as an extending description of standard methods, the so-called multi-dimension characteristics can be introduced and primary characteristic versus time should be extended. Both global and local characteristics of waveform can be obtained in TABLE I.

TABLE I. MULTI-DIMENSION CHARACTERISTICS

Characteristics of entire events	Number of transition segments
	Duration
Characteristics of each transition segments	Phase-angle jump (PAJ)
	Point-on-wave (POW)
Characteristics of each during-event segments	Magnitude
	Unbalance
	Distortion
	Sag type

It is sometimes difficult to calculate duration from magnitude versus time and threshold when magnitude oscillates about threshold level. Especially in practical application, traditional method would miscount sag events even if hysteresis voltage is introduced. By the help of segmentation, the oscillation considered as transition segment which would not trigger threshold again. As a clear boundary between pre-event and during-event state, transition segment is helpful for some characteristics associated with fast variation of magnitude and phase-angle, such as phase-angle jump (PAJ) and point-on-wave (POW) [10], [17]. Considering that sag events sometimes are multi-stage, there are several during-event segments divided by transition segments. Except for single magnitude value, more waveform characteristics can be calculated in each during-event characteristics. These additional characteristics are valuable for the information about underlying causes and states of power system. It is noted that the research in this paper is focused on the segmentation method and its impact on characteristics instead of characteristics calculation itself, and detection result with or not with segmentation method will be discussed in section V.

III. AUTOMATIC SEGMENTATION BASED ON SINGULAR VALUE DECOMPOSITION

A. *ABC-dq transform and mathematic morphology*

Obviously, not only voltage magnitude versus time but phase angle is required in detection process, which makes RMS detection algorithm inappropriate. This traditional method presents one cycle historical average value, not instantaneous value, which may lead to time delay and cannot detect phase angle jump. Seen from the Annex of IEC Std 61000-4-30, it is known that RMS voltage values correctly reflect the available power into a resistive load, but electronic loads are not directly sensitive to RMS voltage, instead, they may be sensitive to additional characteristics. Considering time resolution and real-time characteristics, instantaneous voltage *dq* transform based on the instantaneous power theory is implied, which transforms *abc* three-phase voltages into the *dq* two dimensional instantaneous voltages. Considering the characteristic of three-phase three wire circuits, a fictitious three-phase system is created from reference single-phase voltage. Finally, *dq* two dimensional components are obtained from *abc* three-phase voltages. How to pick up dc component accurately is the key of getting magnitude and phase-angle of voltage sag. Mathematical morphology is a subject based on set theory and integral geometry, where the most common

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operations are dilation, erosion. Combining dilation and erosion operation can construct two different morphological transformations according to the sequence of combination, i.e., opening and closing operation, which are expressed in (1).

$$\begin{aligned}(f \circ g)(n) &= (f \Theta g \oplus g)(n)\\ (f \bullet g)(n) &= (f \oplus g \Theta g)(n)\end{aligned} \tag{1}$$

Opening operation can be used to filter out the peak noise above signal and remove the burr and the litter bridge structure; while closing operation can be used to smooth or inhibit the trough noise behind signal and filter the litter groove structure. Taking the advantage of both operations into consideration, two alternating filters are generated in (2).

$$\begin{aligned}[(f)oc(g)](n) &= (f \circ g \bullet g)(n)\\ [(f)co(g)](n) &= (f \bullet g \circ g)(n)\end{aligned} \tag{2}$$

An alternate-hybrid filter based on these filters above can be expressed as follow.

$$[(f)ah(g)](n) = [(f)oc(g) + (f)co(g)](n)/2 \tag{3}$$

The selection of structural element is important and the shape and size of which will have a direct impact on monitoring accuracy, dynamic response speed, and the calculation speed of monitoring system. There are many kinds of structural elements, such as straight element, curve element, triangle, round and others. To extracted dc component after *dq* transform, the line structural element is selected.

B. Adaptive automatic segmentation based on singular value decomposition method

Singular points are those instants where monitoring signal discontinuities. For power quality disturbance data, the singular point is often associated with a sudden change in system, that is, transition segment. Assume $A \in R^{m\times n}$ ($m \geq n$), and there are matrix $\boldsymbol{U}$ and $\boldsymbol{V}$ named left and right singular vectors of $\boldsymbol{A}$, respectively.

$$\begin{aligned}U &= [u_1, u_2, \cdots u_m] \in R^{m\times m}, U^T U = I\\ V &= [v_1, v_2, \cdots v_n] \in R^{n\times n}, V^T V = I\end{aligned} \tag{4}$$

Matrix $\boldsymbol{A}$ can be factored as

$$A = USV^T \tag{5}$$

where $A = diag(\lambda_1, \lambda_2, \cdots, \lambda_n)$ with $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_n$. The singular values λ_i describe the significance of individual singular vectors in the composition of the matrix. The singular vectors corresponding to the larger singular values have more contribution to the structure of patterns embedded in the matrix than the other singular vectors.

The reason that why automatic segmentation is difficult is that the variety of threshold may lead to different results, which makes threshold-selecting important. Due to the stochasticity of sag events, a reasonable fixed threshold for one recording waveform may be unavailable for another one. Aiming at this defect in exceeding automatic segmentation, a feasible solution is extending the accurate range of threshold-selecting and another one is change it adaptively. The presented method combined both of them and proposed a two-stage segmentation process.

According to the specialty that voltage magnitude in transition process always changes abruptly and fast, SVD is implied to locate the boundaries automatically. As shown in Fig.2, singular values in transition segment are significantly larger than others, where boundaries of transition segments are determined with threshold. In Fig.2, if the threshold is larger than S1, transition segment cannot be detected. On the contrary, more segments may false trigger if the threshold is lower than S3, while S2 seems to be appropriate. Therefore, threshold between S1 and S3 may meet the requirement and this range is usually large which means it is much easier to select threshold based on SVD.

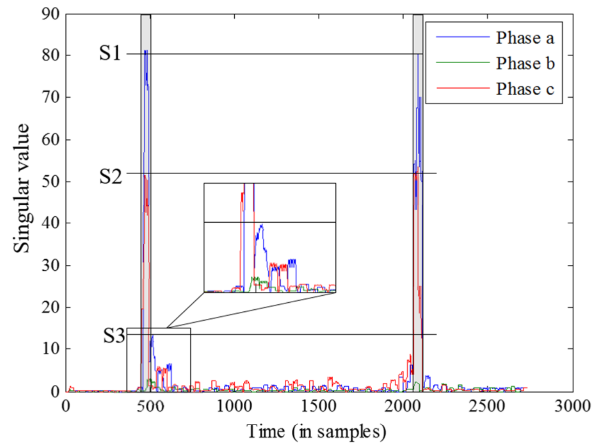

Figure 2. The singular value of sag events

Actually, unlike pre- and post-event segment, voltage magnitude in during-event segment sometimes has oscillation and fluctuation which increase the singular value of during-event segment. If the threshold is too low, some fluctuations may lead to false alarm whereas small sag depth may lead to miss alarm. Therefore, the threshold should not be fixed in different sag events. The proposed method divides recording waveforms by two stages. In the first stage, the initial threshold is selected lower than S1. Due to the range of appropriate threshold is large, the different threshold values may not lead to various segmentation results. Even if the threshold is lower than S3 in Fig.2, the false trigger will be corrected in the next stage. In the second stage, characteristic like variance of singular value in the first or last transition segment is utilized as reference to calculate adaptive threshold, and then final segmentation result is determined. The flow chart is illustrated in Fig.3. In view of the computing resource and practicability, the progress is divided into two parts, namely on-line and off-line respectively.

IV. PERFORMANCE OF THE PROPOSED ALGORITHM

A. Performance analysis of segmentation

It is known that threshold plays an important role in detecting problem, and receiver operating characteristic (ROC) analysis is applied to evaluate the influence of it [15], [16]. The detection progress can be considered as a binary hypothesis problem, where whether there is transition segment can be labeled as “positive” versus “negative”, or “true” versus “false”.

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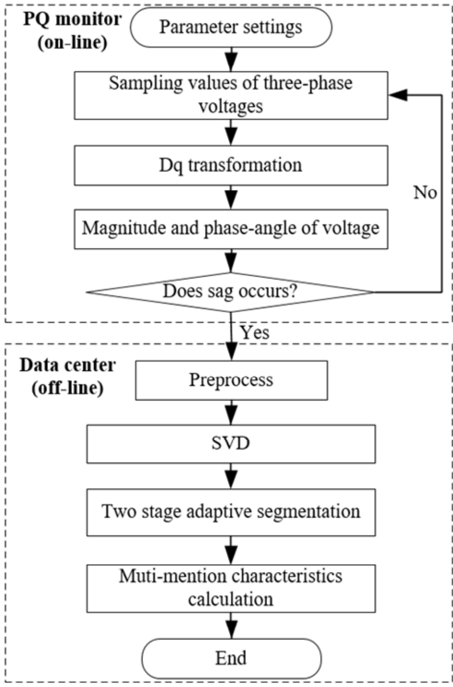

Figure 3. The flow chart for proposed algorithm

In ROC analysis, the detection of each sag waveform is compared to its true result. This comparison is familiar to all cases because it is same comparison with which the familiar performance measures of sensitivity and specifity are calculated. Sensitivity is simply the propotion of correctly detected cases among all of those that are truly positive, namely True Postive Ratio (TPR). And specifity is the proportion of correctly classified cases among all of thoes that are truly negative, which is calculated by one minus False Positive Ratio (FPR). Use sensitivity and FPR as coordinates, which can be obtained in (6)-(7), the ROC curve is obtained. Performing the detection of each waveform is associated with uncertainty, so that sensitivity and specifity can not be both 100%. Actually, there is usually a trade-off between sensitivity and specifity depending on the threshold.

$$TPR = \frac{TP}{TP + FN} \tag{6}$$

$$FPR = \frac{FP}{FP + TN} \tag{7}$$

Three methods have been compared by applying them to 68 recorded waveforms in field and 40 synthetic waveforms. The first method M1 is based on the first-order deviation of fundamental magnitude [9], M2 is based on the Kalman filter [8], and M3 is the proposed method based on automatic segmentation in this paper. ROC curves are illustrated in Fig.4, where each point represents the sensitivity and FPR of specific threshold. If threshold is too low, sensitivity and FPR are both closed to 100%, that is, nearly all true cases can be detected but many false cases lead to false alarm; on contrast, sensitivity and FPR are both closed to 0%, which means nearly all false cases can be avoided, but many true cases are missed too. Sevral points are ploted by change threshold and ROC curve is fitted. If curve is closer to upper left corner, the segmentation is better. Therefore, the area under curve (AUC) is commonly utilized as a global indicator of tectection performance, which is equal to the probability that algorithm can correctly detect whether there is segment. The AUC of M1, M2 and M3 is 92.72%, 94.40% and 95.62% respectively. In Fig.4, it is obvious that M2 and M3 has better performance than M1 especially in higher threshold. The reason that M1 is close to M2 in lower threshold is that RMS get rid of fluctation of waveform and smooth it with the calculation window. So there are fewer false alarm cases and move M1 curve to left. In general, M1 is simpler than M2, whereas the accuraccy of segmenation is worse. As for M3, due to presented adaptive segmentation, the performance is better than M2 especially in lower threshold, that is, the FPR does not increase along with sensitivity. The vertical line indicates large range of threshold selecting and false alarm cases are eliminated by the second stage segmentation mentioned before. The gray area in Fig.4 indicates the main reason why AUC of M3 is larger than M2. In conclusion, the performance of proposed algorithm has been validated.

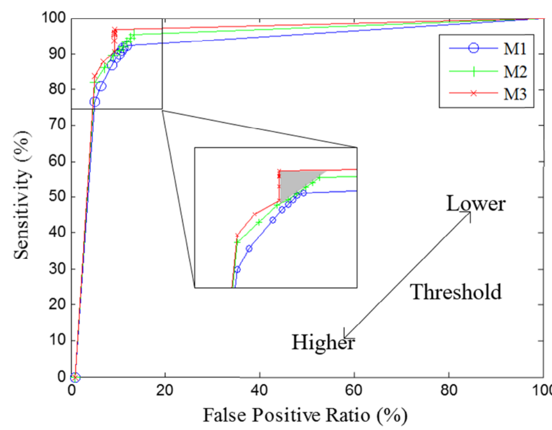

Figure 4. ROC curves plotted from recording data and systhetic data.

B. *Multi-dimension characterization*

100 synthetic waveforms, generated by electric power standard source, are implemented to verify the accuracy of detection algorithm. Related parameters about case study are provided in TABLE II. Take a two-stage voltage sag as an example, the duration of entire events is 8 cycles, and magnitude of two stages are 147kV and 100kV as well as PAJ of two stages are ±15° and ±60° respectively. As mentioned before, TABLE III provides multi-dimension characteristics of the waveform.

TABLE II. PARAMETERS ABOUT CASE STUDY

System frequency	50Hz
Voltage sag threshold	0.9 p.u.
Type of sag events	LG, LL, LLG, LLL
Sample frequency	4.8kHz
Harmonic	Hd3=5%, Hd5=5%, Hd7=5%

TABLE III. MULTI-DIMENSION CHARACTERISITCS

Multi-dimension characteristics		Detecting result	Error
Number of transition segments		3	--
Duration (cycles)	Start time	8.20	0.20
	End time	16.17	0.17
Magnitude (kV)	1st during-event segment	147.27	0.12%
	2nd during-event segment	100.41	0.18%
PAJ (°)	1st transition segment	0.00;-14.20:15.97	0.00;0.80;0.97
	2nd transition segment	0.00;-59.97;59.81	0.00;0.03;-0.19
Sag type	1st during-event segment	Ca	--
	2nd during-event segment	Ca	--

To validate the reliability of proposed algorithm, 100 synthetic waveforms are implied, and detection results of basic characteristics are shown in Fig. 5. It can be seen that detecting error of both magnitude and duration are meet the requirement of standard [1][4].

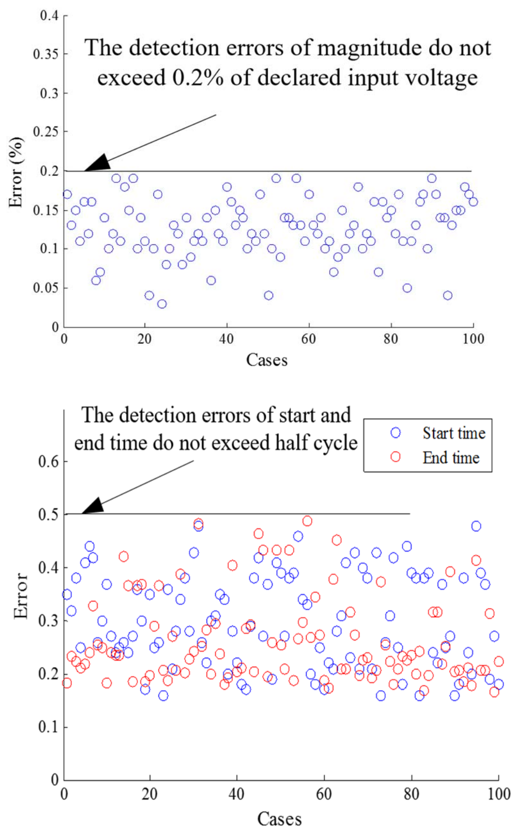

Figure 5. Result of characterization: magnitude (above); duration (down).

Due to the limit of space, the calculation of some other characteristics will not be discussed [9][10] and one should bear in mind that this paper focuses on the segmentation and its impact on calculation of characteristics rather than the calculation method itself.

V. Conclusion

In this paper, an approach for the detection of voltage sag and automatic segmentation has been presented. As an extending way of traditional characterization method, additional characteristics such as PAJ, sag type and so on are considered. The difficulty that how to locate boundaries of transition segment automatically is overcome through two stage adaptive segmentation based on SVD method. Results show that it can effectively detect transition segments and the performance is better than existing automatic segmentation method. Besides, calculation of basic characteristics meet requirement of standard and some additional characteristics can be obtained.

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