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Complex power quality disturbances classification via curvelet transform and deep learning

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A B S T R A C T

This paper presents a novel approach to detect and classify the power quality disturbance (PQD) signals based on singular spectrum analysis (SSA), curvelet transform (CT) and deep convolutional neural networks (DCNNs). SSA is a non-parametric technique, does not require any supposition to generate the observed signal, and provides an effective way to recognize weak transient PQ signal. Fast discrete curvelet transform (FDCT) is an efficient method compared to wavelet transforms. Firstly, PQD signals are decomposed using SSA and FDCT methods. Initial six and three levels decomposition of the SSA and FDCT are used as features of PQD respectively. Finally, DCNNs based classifier and multiclass support vector machines (SVMs) classifier are used for classification of single and complex PQDs. For validation of the proposed algorithm, thirty-one categories of real and synthetic PQD waveforms are considered. The proposed scheme is tested and the results are recorded. The results of proposed SSA-FDCT-DCNN (SFD) based classifier are compared to the results of multiclass SVM based and other existing methods The achieved results show that the SFD classifier is more proficient than the multiclass SVM and other present methods. In addition, the proposed SFD based classifier can be efficiently used to classify the single and complex PQ disturbances.

1. Introduction

Based on the IEEE power quality disturbances (PQDs) standard, the PQDs are depended on frequency, time and magnitude of voltage and or current. For detection, localization, and classification of PQDs, many methods have been presented. The PQDs can be classified into two categories such as stationary and nonstationary signals. Mostly, PQDs are nonstationary in nature because continually load changing and switching of the circuits, etc. In recent decades, time and frequency domain methods have been revealed for analyzing of PQDs [1–5].

Fourier transforms (FT), discrete Fourier transform (DFT), short-time Fourier transform (STFT), fast Fourier transform (FFT) and wavelet transform (WT) are the basic techniques for analyzing of PQD. The FT has been using to analyze the stationary PQ signals. STFT is the extension of DFT which is insufficient for the analysis of the non-stationary signal because of its fixed window size. The limitations of STFT have been addressed using wavelet transform. Families of FT are not feasible to analyze the nonstationary PQ signals, and DFT has some weakness for example spectrum leakage and resolution. The main drawback of STFT is that it cannot use long window size at low frequencies and short window size at high frequencies [6–15].

Typically, the families of wavelet transform have been used to analyze the PQ signals [9,12,15,16]. DWT is the extended version of WT and it upgraded into discrete wavelet packet transform (DWPT). PQD signal can be decomposed into different uniform frequency bands by multiresolution wavelet transform, and it has been used to calculate the root mean square values, distortion index and total harmonic distortion [17–22]. Furthermore, choice of appropriate mother wavelet and the sampling frequency is one of the critical issues to extract suitable frequency components [23–25].

The S-transform is the extension of Fourier and wavelet transforms and can be related to the WT and STFT. The ST is suitable for localizing of PQD, but it is not appropriate for complex order harmonic analysis [7,26]. ST is a dominant technique for analyzing of PQD; nevertheless, it has some significant disadvantages such as the redundant representation of the time–frequency domain. PQ disturbances have been investigated using many other techniques such as compressive sensing (CS), S-transform, Kalman filter, curvelet Transform (CT), Hilbert transform (HT), Hilbert–Haung transform (HHT), hybrid transform-based methods, Gabor transform, Wigner distribution function, and over-complete hybrid dictionaries [1,2,27–32].

The SSA is an innovative method for time series analysis and signal processing [33–35]. SSA has been used for amplitude and phase modulation of a signal [36]. The goals of SSA is to decompose a time series

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signal into the sum of a small number of comprehensible signals, for example, a bit by bit fluctuating trend, periodic or quasi-periodic, oscillatory signals and noise, based on multivariate statistics and linear algebra [33,37,38]. These signals can be used for feature extraction, pre-processing procedure, missing data-point interruption, filtering, and detection [39,40]. Multivariate SSA is the extension of SSA and has been applied in different fields such as food production process, weather forecasting, chemical process, wind prediction and ECG [36,41–45].

Curvelet transform (CT) was proposed by Candes and Donoho [46–48]. In Ref. [48] discriminative studies have been presented between CT and WT, WT works well in demonstrating point singularities. The CT works in curvilinear singularities while does not depend on the existence of any map of the discontinuity set. It is a multiscale pyramid with numerous positions and directions at each length scale. It has useful geometric and work well comparatively WT [46,49]. In this paper, wrapping method is employed for feature extraction of PQ disturbances for the reason that it takes low computational time rather than the unequally-spaced fast Fourier transforms (USFFT) method [46].

Second most important part of the classification of PQ disturbance is that feature selection and choosing of the appropriate classifier [50]. In the literature, preprocessed signals or statistical indices have been used direct input into a classifier [51–55]. In the classification of PQ disturbances, the dimensionality of the extracted feature performances most critical role in the classification domain [56,57]. In this paper, deep convolutional neural network (DCNN) based classifier is proposed for classification of PQD, and dropout is used to overfitting the training [58]. In recent years, DCNNs have been established for automatically learning the feature from a large-scale dataset and achieved notable performance in object recognition. Alex proposed a novel learning method and its incredible performance on 1000 categories of images [59]. Most recent DCCNs methods were proposed for object recognition, and these architectures improved recognition rate [60–62].

In this research work, integrated multivariate singular spectrum analysis (MSSA) and curvelet transform are proposed for feature extraction of PQ disturbance signals. The proposed feature extraction scheme is divided into two steps. Firstly, trajectory matrix algorithm is employed to construct the lag-covariance matrix of the PQD signal. Finally, the CT and MSSA algorithms are utilized to decompose the signal. The CT coefficients have different frequency bands. In this paper, six frequency bands are constructed, and initial three frequency bands are used as the feature of PQD. The higher frequency bands are neglected. Usually, the higher frequency bands constants noise. The MSSA is used to decompose the small transient PQD signals. The transient signals are decomposed into six level. These decomposed signals are considered as PQD features. These extracted features are directly fed into DCCN and multiclass support vector machine algorithms for classification of single and complex PQD signals.

Organization of the paper: In the next section, discussed the proposed method based on singular spectrum analysis, curvelet transform, deep convolutional neural networks and multiclass support vector machines. Section 3 describes the experiment. Section 4 presents results and discussions, and Section 5 concludes the paper.

2. Methodology for feature extraction and classification

In this work, a novel technique is introduced to extract feature vector of original PQD signal based on fast discrete curvelet transform, singular spectrum analysis, and deep learning.

2.1. Multivariate singular spectrum analysis

The multivariate singular spectrum analysis (MSSA) [36,41] method comprises of typically four steps, 1. embedding (construction of trajectory matrix), 2. decomposition of signal, 3. eigen-triple grouping

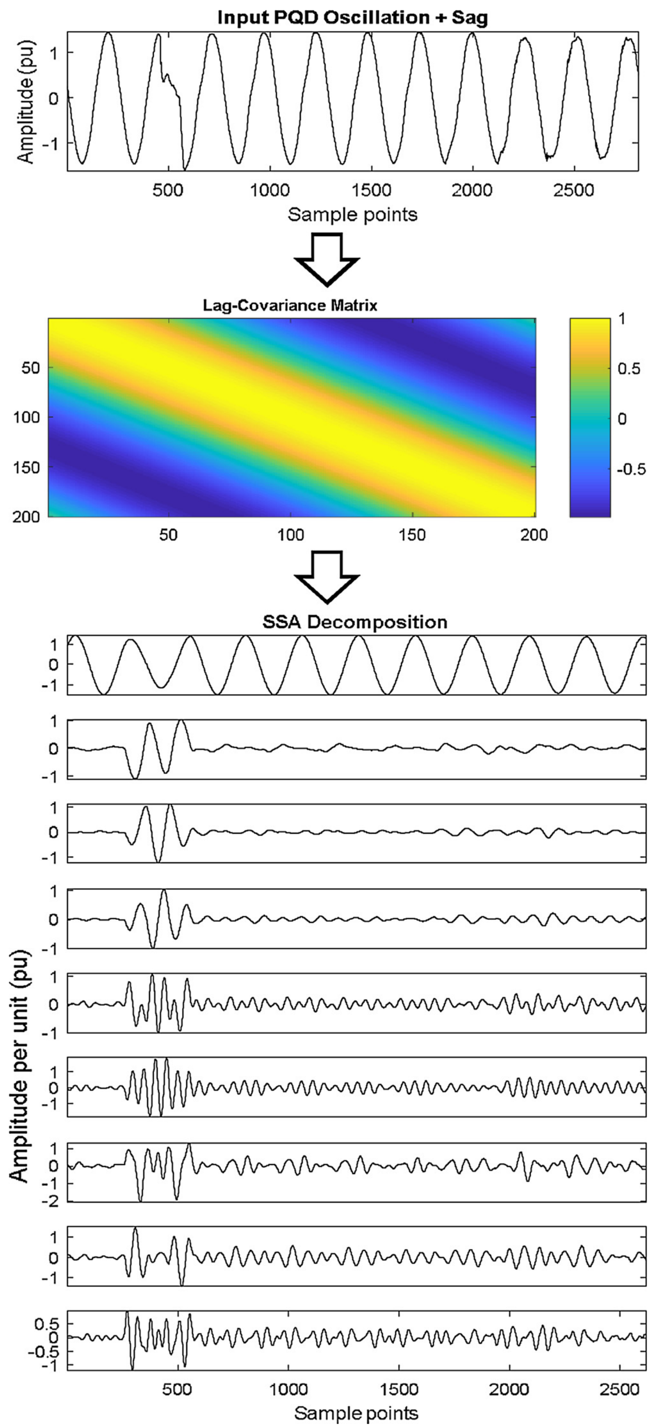

Fig. 1. PQD signal decomposition based on SSA technique.

and, 4. recovery of the signal.

Consider a uniformly sampled power quality disturbance signal in time domain $x(t)$, N_t is the number samples in each time series of PQD signal and m is embedding dimension of trajectory matrix. The trajectory matrix $X^{N\times m}$ can be constructed as $X_{ij} = x_{i+j-1}$, where $1 \le j \le m$ and $1 \le i \le N = N_t - m + 1$. The trajectory matrix holds the entire information of the disturbance signal that has happened within a window of size m.

Lagged-covariance matrix (LCM) can be constructed in different ways. In here, LCM has been constructed by trajectory method. The product of the trajectory matrix and its transpose is known as LCM. It can be built as $S = XX^T = \frac{1}{N}\sum_{i=1}^{N} v_i v_i^T$ and its dimensions are $m \times m$.