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Classification of Power Quality Disturbance Based on Multiscale Singular Spectral Analysis and Multi Resolution Wavelet Transforms

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***Abstract:** In real power system, Power quality disturbances (PQDs) have become major challenge due to the introduction of renewable energy resources and embedded power systems. In this research, two novel feature extraction methods multi resolution analysis wavelet transform (MRA-WT) and Multiscale singular spectral analysis (MSSA) have been analysed with convolution neural network classifier for the classification of PQDs. Statistical parameters are also applied for the optimal feature selection. MSSA is time-series tool and MRA-WT are applied for feature extraction and 1-dimensional CNN (1-DCNN) is used to classify the single and multiple PQDs. The architecture is built with forward propagation and back propagation is utilized to tune the data. Finally, the results of two selected feature extraction techniques are compared with classification accuracy. The simulation based results explained that MSSA with 1-DCNN has significantly higher classification accuracy under different noisy conditions.*

***Keywords:** Power quality disturbance, multiscale singular spectral analysis, multi resolution analysis wavelet transforms, convolutional neural network*

I. INTRODUCTION

Powerquality (PQ) monitoring is essential part in real power system, embedded generation system and high voltage alternative current (HVAC) systems[1].In general, Power Quality Disturbances (PQDs) are non-stationary in nature and occurred due to capacitor switching, non-linear loads. Many techniques have been assessed for the monitoring and identification of PQDs[2-4]. However, the monitoring and classification process consists of three steps: feature extraction, feature selection and classification. Many signal processing techniques have been assessed such as, Fourier transform (FT), Fast Fourier transform (FFT), Short-time Fourier transform (STFT) and Discrete Fourier transform (DFT) for the detection and feature extraction[5-7].Wavelet and multiresolution analysis (MRA-WT) is one of the traditional signal processing techniques, which provides variable size window such as a long window for low-frequency components and short window for high-frequency components. As a result, it provides excellent time-frequency resolution [8]. WT helps to analyze the PQ event and classifying the low and high-frequency issues of PQ disturbances. However, the calculation of appropriate sampling frequency and mother wavelet is one of the key issues that arise in WT to find out the suitable frequency components.Singular spectral analysis (SSA) based on M lagged copies of time series. The estimation of the correlation matrix relies on Karhunen-Loève decomposition. The eigenvectors of this matrix are called empirical orthogonal functions (EOFs) [9]. SSA decomposes the time-series signal into various fluctuation trends, a small number of signals, oscillation, and noises. Instead of reducing the dimension of data, SSA smooths the spectral profile of given data which improves the feature extraction, and classification accuracy can be enhanced accordingly [10, 11]. Additionally, Multiscale SSA (MSSA) is the extension of SSA and applied to many applications such as hyperspectral imaging(HIS), bearing fault diagnosis physiological signals, geophysics, murmur detection of a heart sound, vibration signal, and economic data [12-17]. In this study, twelve type of single and multiple PQDs has been assessed with MSSA, MRA-WT with 1 Dimensional-Convolutional Neural Network (1D-CNN). Firstly, two feature extraction techniques MSSA and WT-MRA is used for feature extraction and statistical parameters such as energy, entropy, mean, standard deviation, skewness and kurtosis has been used for optimal feature selection and lastly, this optimally selected feature set is fed to 1D-CNN classifier for the efficient classification of PQDs. The rest of the paper is organized as Section 2 provides the detail about the proposed feature extraction, selection and classification methods, section 3 gives the detail about the experiment, section 4 provides the detail about results and discussion and section 5 concludes the work.

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II. PROPOSED METHOD FOR THE FEATURE EXTRACTION AND CLASSIFICATION

A. Multiscale Singular Spectral analysis

In SSA, any time-series signal X is analyzed with the largest scale of length N and the largest period is M.

As a result, lagged correlation matrix C contains the information of the whole time series. Time-frequency analysis is introduced in the SSA methodology. The window size W is proportional to the order M of the correlation matrix. Multiscale representation of the respective data can be obtained by varying the M and W. For a given position of b and fixed W, the varying windows of length $W \leq N$, center on time scale $b = \frac{1}{2}W, \dots, N - \frac{1}{2}W$. These two scales W and M can be varied independently, as soon as we get W is larger than M, $\frac{W}{M} \geq \alpha > 1$. It can obtain local EOFs of which Singular Value Decomposition(SVD) or reconstruction (grouping, diagonal averaging) can be computed. The EOFs and the analysing function of wavelet (Mother wavelet) are the analogs. Assume that we have PQ event, which is a 1-D signal in a vector array A define as $A = [a_1, a_{2,\dots,} a_N]^T \in \Re^N$ of length N where N is $b - \frac{1}{2}W \leq i \leq b + \frac{1}{2}W$.where b is the position and window size W $(1 < W < N)$. The trajectory matrix C of the matrix A can be formulated from the following formula

$$C_{kl} = \frac{1}{N - |l - k|} \sum_{t=1}^{N-|l-k|} V(t)V(t + |l - k| \qquad (1)$$

Each column of C mapped to lagged vector K, that is $c_K = [a_k, a_{k+1}, \dots, a_{k-L+1}]^T \in \Re^L$, where $k \in [1, K]$ and $K = N - W + 1$. from trajectory matrix C, S lag- covariance matrix is obtained as

$$S = CC^T \qquad (2)$$

its eigenvalues are calculated and sort in descending order as, $(\lambda_1 \geq \lambda_2 \geq \cdots \lambda_L \geq 0)$ and equivalent eigenvectors be $(U_1, U_2, \dots, U_L)$, and the trajectory matrix after SVD is presented as

$$C = C_1 + C_2 +, \dots, C_d \qquad (3)$$

Where $d \leq W$ is the rank of matrix C but for simplicity, we consider $d = W$. As it can be noted, trajectory matrix C is a combination of several matrices. The decomposition can be formulated as

$$d_i(t) = \sum_{k=1}^{P} V(t + k - 1)EoF(k) \qquad (4)$$

Where P, is the number of decomposition level of PQDs and $EoF(k)$ is called empirical orthogonal function (EoF) and decomposition of PQD signal using MSSA is shown in Fig. 1.

B. Multiresolution analysis based Wavelet Transform

In general, PQDs are formed due to the poor grounding, non-linear load and capacitor banks and wavelet transform (WT) is excellent for analyzing the typical PQDs. In this study, MRA based wavelet decomposition is presented. Fig. 2 demonstrates the detailed mechanism of DWT. The high-frequency component (detail coefficients) are provided by the HP filters of their respective level (D1) and LP filter provides the low-frequency component (approximation coefficients A1) of the discrete-time signal, followed by the process of down-sampling by 2. the scale $\varphi(t)$ and wavelet $\omega(t)$ of approximate l and detail coefficients h for a signal x[n]can be represented as:

$$\varphi(t) = \sqrt{2}\sum_n h(n)\varphi(2t - n) \qquad (5)$$

$$\omega(t) = \sqrt{2}\sum_n l(n)\omega(2t - n) \qquad (6)$$

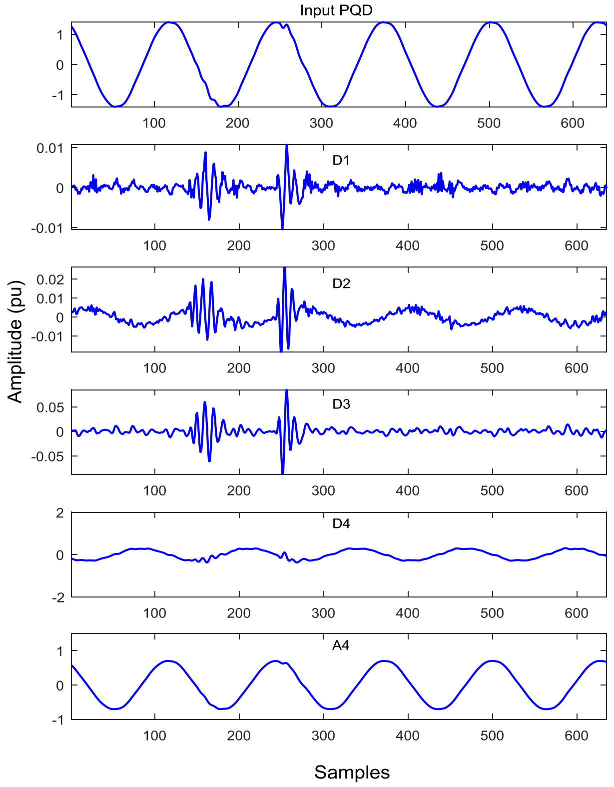


Fig. 1.PQD decomposition using MSSA

Secondly, in the next level, the A_g is set as $x[n]$ and g_m is increased by 1. The above mention process repeats until g reached the limit of the selected number of levels, as shown in Fig. 2.

The multiresolution analysis (MRA), is applied to decompose the PQDs signal. Suppose A(n) is the input discrete signal and it decompose into detail signal $\mathrm{d(n)} = \sum_{k=1}^{l} \mathrm{d_k(n)}$, where n is the number of sample of the signal, $\mathrm{k} = 1,2,3, \dots, \mathrm{l}$ and approximation signal a and signal is formed as

$$\mathrm{A(n)} = \sum_{k=1}^{l} \mathrm{d_k(n)} + \mathrm{a_l} \qquad (7)$$

Where, l is the number of decomposition level. The feature representation of PQDs using MRA-WT is presented in Fig. 2.

C. Comparison MSSA and MRA-WT

The comparison between MSSA and MRA-WT are presented in Fig. 1, and 2. Moreover, analogies between SSA and wavelet transform (WT) were shown in [18, 19].

Table I shows the use of mathematical parallels between SSA and WT.

The MSSSA algorithm consists of two main stages decomposition and reconstruction.

D. Feature Extraction

The efficient feature extraction from the preprocess PQDs is very important to improve the classification accuracy [20]. In this paper, features are extracted and selected through the MSSA, MRA-WT and statistical parameters. The use of all input data coefficient may decrease the classification accuracy and increase the computation load. Therefore, the statistical parameters such as energy, entropy, standard deviation, mean, kurtosis, and skewness are chosen [5, 21]. For each decomposition technique, the total number of features obtained per phase is 24 for MSSA and MRA-WT decomposition technique. The mathematical relationship of these statistical parameters are given in Table II.Where, $X = \{x_1, x_2, \ldots, x_N\}$ are the sub-bands, where N is the length or number of samples in sub-band.

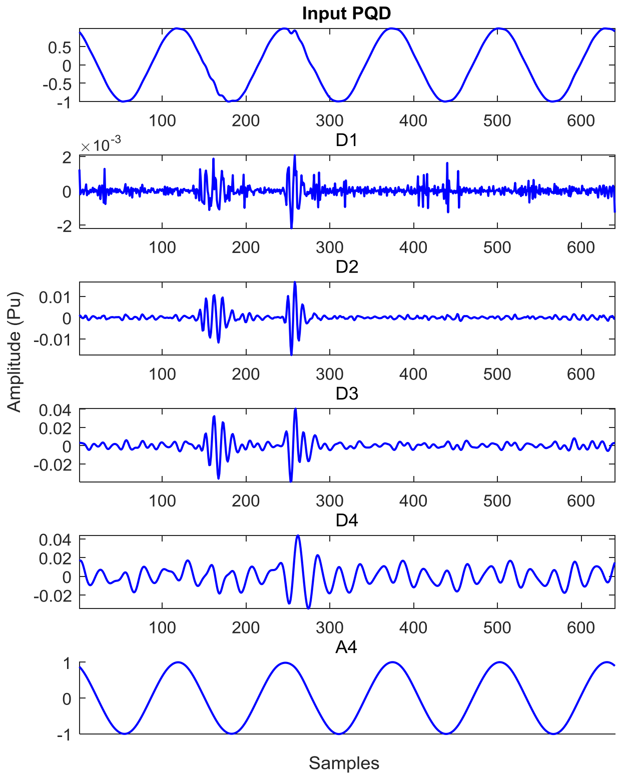


Fig. 2. PQD decompostion using MRA-WT

Table- I: Similarity between SSA and Wavelet transform

	SSA	Wavelet transform
Analyzing Function	*Eof* $\boldsymbol{\rho}$	*Mother Wavelet* $\boldsymbol{\psi}$
Basic Fact	EOF Eigenvectors of C	$\boldsymbol{\psi}$ Chosen a Priori
Decomposition	$X_l = \sqrt{\lambda_l} u_l^b (v_l^b)^T$	$\int_{-\infty}^{\infty} f(t)\psi_{b;a}(t)\,dt$
Scale	$w = \alpha M$	a
Epoch	t	b

E. Convolutional Neural Network

In a wide context, Convolution neural network (CNN) is feature extraction and classification neural network topology. CNN can become complex with feature extraction and classification capabilities. The complex architecture of CNN can consist of multiple layers that extract different features from the PQDs [22]. Fewer examples of CNN complex architecture for different applications can be seen from the literature [23, 24]. In general, CNN is implemented in 2-dimensional with multi-dimensional kernels and complex configuration. Our network is further refined by adding dropout and regularization [25]. The PQDs data can be classified in single dimension. In this paper, only the classification layer (softmax layer) with max pooled layer is utilized, which make the network simple for the classification of PQDs.

Table- II: Feature extraction using statistical parameters

Statistical Parameters	Mathematical Formulas
Standard Deviation	$\sigma_{ki} = \left(\frac{1}{N}\sum_{j=1}^{N}\left(X_{ij}-\mu_i\right)^2\right)^{\frac{1}{2}}$
Entropy	$ET_{ki} = -\sum_{j=1}^{N} X_{ij}^2 \log\left(X_{ij}^2\right)$
Energy	$E_{ki} = \sum_{j=1}^{N}\left(\lvert X_{ij}\rvert^2\right)$
Kurtosis	$KT_{ki} = \sqrt{\frac{N}{24}}\left(\frac{1}{N}\sum_{j=1}^{N}\left(\frac{X_{ij}-\mu_i}{\sigma_i}\right)^4 - 3\right)$
Skewness	$SN_{ki} = \sqrt{\frac{1}{6N}}\sum_{j=1}^{N}\left(\frac{X_{ij}-\mu_i}{\sigma_i}\right)^3$
Mean	$M_{ki} = \frac{1}{N}\sum_{j=1}^{N} X_{ij}$
`Log-energy Entropy	$LE_{ki} = -\sum_{j=1}^{N}\log\left(X_{ij}^2\right)$

However, the architecture of 1-DCNN comprises of input, the convolution layer connected with network max pooling that feeds to fully connected softmax and output layers that are shown in Fig.3. the initial kernel was set at 24 for MSSA and MRA-WT decompositions. The training process of CNN consists of forward propagation and backpropagation. Forward propagation trains the data for the classification and backpropagation is utilized to upgrade the training parameters to improve the classification accuracy. The complete architecture is presented in Fig. 3.

1) Forward propagation

For (L+1) layer CNN network, m_1 is the input layer and m_7 is the output layer, l is the current layer, $m_2$to m_6 numerous hidden units of convolution layer, max pooling layer, fully connected layers and regularization layer, and expressed as:

$$w_n^l = \sum_{i=1}^{M} w_i^{l-1} * j_{in}^l + b_n^l \tag{8}$$

Where, w_i^{l-1} is the convolution feature map of previous layer.

w_n^l is convolution feature map of current layer, M is the number of input features. b_n^l is the additive bias vector.

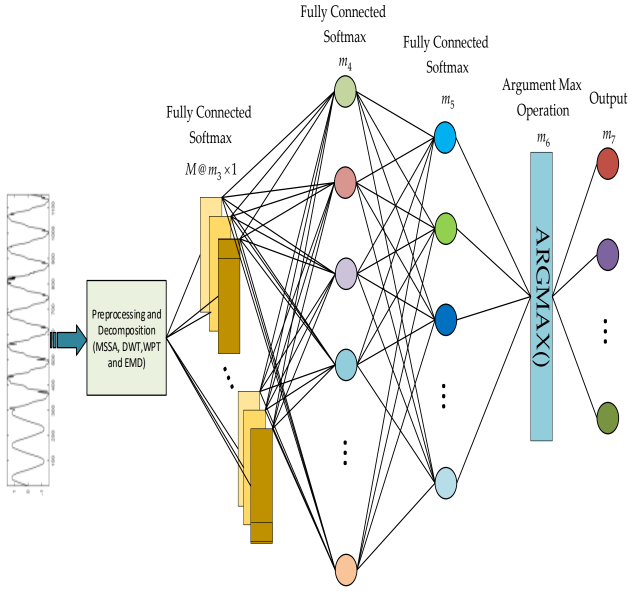
'*' is the convolution operator. The output can be written as

$$z_n^l = f_n\left(w_n^l\right) \tag{9}$$

z_n^l is the output, f_n is the non-linear function, rectified linear units (ReLU) is widely used non-linear operator and used as activation function in this study. The advantage of this function is, it accepts the output of neuron if positive means it does not active all the neurons at the same time and converts all negative inputs to zero, which makes it efficient gradient propagation and low computational burden. *max(w)* function is used in pooling layer, fully connected layer with softmax layer is connected to the output layer as CNN is multiclass classifier, the softmax layer is expressed as:

$$\delta\left(z\right)_n = \frac{e^{z_n}}{\sum_j^J e^{z_j}}, n = 1,\dots,J \tag{10}$$

Where, z_n is the input from fully connected layer, J is the number of classes or softmaxlayer units.



III. EXPERIMENT

Dataset: 12 types of single and combine PQDs have been considered to validate the proposed algorithm. Two different sets of databases are generated. First database is consisted of single PQDs and second type of database is comprised of combined PQDs. 2500 waveforms have been created for single PQQs by changing the respective parameters. 1500 waveforms randomly created for combined PQDs. MATLAB and PSCAD is utilized to generate the PQDs according to the IEEE standards. In real power system, the signals are usually contaminated with noise and in this experiment Gaussian noise is also added from 20 dB to 50 dB and the mathematical model of simulated waveforms are available in the literature [26].

In order to justify the validation of proposed method, some of the real PQDs waveforms are also considered such as, sag and impulsive transient, sag, flicker, notch, sag with impulsive transient with notch, and sag with oscillatory transient and shown in Fig. 4. This algorithm was tested more than 20 times to confirm the classification performance. Training and testing sets were separated by 75% and 25% respectively. The fundamental frequency is 50 Hz and 10 cycles were generated for each PQDs of synthetic dataset. The feature extraction using MSSA and MRA-WT are presented in section 2. The environment used for experiments is MATLAB (R2017a) i7-6700 CPU @ 3.40 GHz and 8 GB RAM.In this research, 1D-CNN is proposed for the classification of PQDs. Forward propagation is utilized to train the dataset and initialization. The process of fine tune is done by the backpropagation.

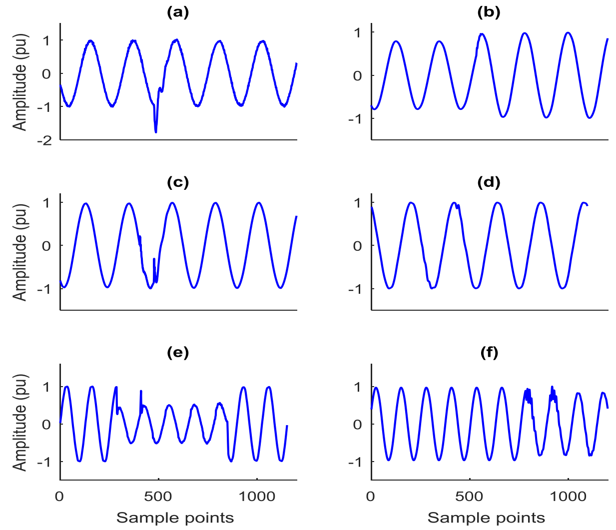


Fig. 4.PQ waveforms IEEE 1159-2009 (a) sag and impulsive transient (b) sag (c) flicker (d) notch (e) sag with impulsive transient with notch (f) sag with oscillatory transient

IV. RESULTS AND DISCUSSION

In this research, synthetic as well as real PQDs waveforms are used to assess the proposed algorithm. One of the main significance of this research, statistical parameters were utilized for optimal feature selection and optimal features are more important than the raw data. The classification accuracy [27]can be evaluated from the following equation.

$$\text{1DCNN\_acc} = \frac{correctly\ classified}{total\ numer\ of\ classes} \times 100 \tag{11}$$

The performance of 1D-CNN is evaluated with optimal features such as energy, entropy, skewness, standard deviation, kurtosis and mean. The average classification accuracy for each class is shown in Table III. The results of MSSA-1D-CNN is compared with MRA-WT-1D-CNN classifier and the detail results for each class for MSSA and MRA-WT is also explained in Table III. The average overall classification accuracy is 99.8 and 98.9% for noiseless and noisy conditions respectively. The classification accuracy of proposed MSSA-1D-CNN with real dataset is shown in Table IV. The results show that MSSA based classifier has superior classification accuracy than MRA-WT based classification method.

The excellent noise immunity ability of MSSA made it more suitable for the classification of real and synthetic PQDs dataset.

A. Performance Comparison

Table V presents a detailed comparison between published articles with the proposed algorithm. In [28], 12 types of single and multiple PQDs were considered and Fast time-time transform (FTT) with small residual extreme learning machine (SR-ELM) were successfully implemented but this method has relatively less classification accuracy than the proposed method. Only nine types of three-phase PQDs were classified with Discrete WT, hyperbolic ST, and SVM and the classification accuracy 99.44 was achieved [29]. However, this article considered less number of PQDs and having less classification accuracy as compared proposed algorithm.

Table-III: Classification accuracies of MRA-WT-1D-CNN and MSSA-1D-CNN for different noise levels

Power Quality Disturbances	Class Labelled	Training/ Testing sets	MRA-WT-1D-CNN				MSSA-1D-CNN			
			0 dB	*50 dB*	*30 dB*	*20 dB*	*0 dB*	*50 dB*	*30 dB*	*20 dB*
Normal	C_1	200	100	99	100	99	100	100	100	100
Sag	C_2	200	100	99	100	99	100	99	100	99
Notch	C_3	200	99	98	99	98.5	100	99	100	99
Flickers	C_4	200	98	97	97.8	97.1	100	99	100	98.8
Impulsive Transients	C_5	200	99	99	98.9	97.9	100	99	99.8	99
Oscillatory Transients	C_6	200	99	98	99	98.5	99	99	99.7	98.7
Harmonics	C_7	200	99	99	98.4	97.3	99.5	99.1	99.6	99
Sag with Swell	C_8	200	99	98	98.1	97.1	100	99.5	99.8	99
Sag with Harmonics	C_9	200	98	98	98	96.9	99.7	98.2	99.6	97.9
Harmonics with Sag and Swell	C_{10}	200	99	98	98.9	97.4	99.6	99.2	99.5	99
Sag with Oscillatory Transients	C_{11}	200	99	99	99	98.3	99.8	99.25	99.3	98.9
Oscillatory Transients with Swell, and Sag	C_{12}	200	99	98	99	98.7	99.7	99.3	99.3	99
Classification Accuracy (%)	-	-	99	98.3	98.8	97.9	99.8	99.12	99.7	98.9

Table- IV: Classification accuracies of MRA-WT-1D-CNN and MSSA-1D-CNN methods for real PQD dataset.

Power quality disturbances	MRA-WT-1D-CNN	MSSA-1D-CNN
Sag	99.62	100
Flicker	99.21	100
Notch	99.05	100
Sag and Impulsive Transient	98.63	99.89
Sag with Impulsive Transient with Notch	97.83	99.55
Sag with Oscillatory Transient	98.55	99.83

In [30], maximum overlapping DWT (MODWT), second-generation WT (SGWT) and ST were compared to accomplish the best classification results. ST retained the best classification rate of 97.39%. This study shows that the proposed study attained higher classification results.

Table- V: Performance Comparison with published articles

Classifier	Data Type	Decomposition methods	No. of PQDs	Accuracy (%)
DT-RF	Simulated	FT, STFT, HT, ST, WT, TTT	16	99.43
SVM	Simulated	OST,MST	19	97.3
RF	Simulated and Real	MODWT, SGWT, ST	10	97.39
HOS, CNN	Simulated and Real	DWT, EMD, WPD, MSSA	12	99.9

V. CONCLUSION

In this study, two feature extraction techniques MSSA and MRA-WT with 1D-CNN based classifier have been presented for detection and classification of 12 type of single and multiple PQDs. Various statistical features have been considered to improve the classification accuracy. The performance of the proposed algorithms has been assessed by the different experiments for synthetic and real datasets and the results show that the proposed MSSA-1D-CNN is better choice for the classification as compared to MRA-WT based method. The proposed method can be used for the application of image processing, heart patient data and other classification applications.

REFERENCES

1. Jianming, Z. and L. Jinjun. Wavelet-based neural network approach for power quality event monitoring and analysis. in 2008 Chinese Control and Decision Conference. 2008. IEEE.
2. Gaing, Z.-L., Wavelet-based neural network for power disturbance recognition and classification. IEEE transactions on power delivery, 2004. **19**(4): p. 1560-1568.
3. Morsi, W.G. and M. El-Hawary, Wavelet packet transform-based power quality indices for balanced and unbalanced three-phase systems under stationary or nonstationary operating conditions. IEEE Transactions on power delivery, 2009. **24**(4): p. 2300-2310.
4. Masoum, M., S. Jamali, and N. Ghaffarzadeh, Detection and classification of power quality disturbances using discrete wavelet transform and wavelet networks. IET Science, Measurement & Technology, 2010. **4**(4): p. 193-205.
5. Santoso, S., et al., Characterization of distribution power quality events with Fourier and wavelet transforms. IEEE Transactions on Power Delivery, 2000. **15**(1): p. 247-254.

6. Heydt, G., et al., Applications of the windowed FFT to electric power quality assessment. IEEE Transactions on Power Delivery, 1999. **14**(4): p. 1411-1416.
7. Wright, P.S., Short-time Fourier transforms and Wigner-Ville distributions applied to the calibration of power frequency harmonic analyzers. IEEE transactions on instrumentation and measurement, 1999. **48**(2): p. 475-478.
8. Gaouda, A., et al., Power quality detection and classification using wavelet-multiresolution signal decomposition. IEEE Transactions on power delivery, 1999. **14**(4): p. 1469-1476.
9. Vautard, R., P. Yiou, and M. Ghil, Singular-spectrum analysis: A toolkit for short, noisy chaotic signals. Physica D: Nonlinear Phenomena, 1992. **58**(1-4): p. 95-126.
10. Chu, M.T., M.M. Lin, and L. Wang, A study of singular spectrum analysis with global optimization techniques. Journal of Global Optimization, 2014. **60**(3): p. 551-574.
11. Elsner, J.B. and A.A. Tsonis, Singular spectrum analysis: a new tool in time series analysis. 2013: Springer Science & Business Media.
12. Muruganatham, B., et al., Roller element bearing fault diagnosis using singular spectrum analysis. Mechanical systems and signal processing, 2013. **35**(1-2): p. 150-166.
13. Schoellhamer, D.H., Singular spectrum analysis for time series with missing data. Geophysical Research Letters, 2001. **28**(16): p. 3187-3190.
14. Zabalza, J., et al., Singular spectrum analysis for effective feature extraction in hyperspectral imaging. IEEE Geoscience and Remote Sensing Letters, 2014. **11**(11): p. 1886-1890.
15. Sanei, S., M. Ghodsi, and H. Hassani, An adaptive singular spectrum analysis approach to murmur detection from heart sounds. Medical engineering & physics, 2011. **33**(3): p. 362-367.
16. Hassani, H. and A. Zhigljavsky, Singular spectrum analysis: methodology and application to economics data. Journal of Systems Science and Complexity, 2009. **22**(3): p. 372-394.
17. Salgado, D. and F. Alonso, Tool wear detection in turning operations using singular spectrum analysis. Journal of Materials Processing Technology, 2006. **171**(3): p. 451-458.
18. Yiou, P., Dynamique du paléoclimat: Des données et des modeles. 1994, Ph. D. thesis, 183 pp., Univ. Pierre et Marie Curie, Paris.
19. Ghil, M. and C. Taricco, Advanced spectral analysis methods. Past and present variability of the solar-terrestrial system: measurement, data analysis and theoretical models, 1997: p. 137-159.
20. Saini, M.K. and R. Kapoor, Classification of power quality events–a review. International Journal of Electrical Power & Energy Systems, 2012. **43**(1): p. 11-19.
21. Abubakar, M., et al., Identification of Multiple Power Quality Disturbances Problems in Wind-Grid Integration System. International Journal of Renewable Energy Research (IJRER), 2019. **9**(3): p. 1406-1417.
22. Hu, W., et al., Deep convolutional neural networks for hyperspectral image classification. Journal of Sensors, 2015. **2015**.
23. Kiranyaz, S., T. Ince, and M. Gabbouj, Real-time patient-specific ECG classification by 1-D convolutional neural networks. IEEE Transactions on Biomedical Engineering, 2015. **63**(3): p. 664-675.
24. Szegedy, C., et al. Going deeper with convolutions. in Proceedings of the IEEE conference on computer vision and pattern recognition. 2015.
25. Srivastava, N., et al., Dropout: a simple way to prevent neural networks from overfitting. The journal of machine learning research, 2014. **15**(1): p. 1929-1958.
26. Shen, Y., et al., Power Quality Disturbance Monitoring and Classification Based on Improved PCA and Convolution Neural Network for Wind-Grid Distribution Systems. Energies, 2019. **12**(7): p. 1280.
27. Ahila, R., V. Sadasivam, and K. Manimala, Particle swarm optimization-based feature selection and parameter optimization for power system disturbances classification. Applied Artificial Intelligence, 2012. **26**(9): p. 832-861.
28. Saini, M.K. and R.K. Beniwal, Detection and classification of power quality disturbances in wind-grid integrated system using fast time-time transform and small residual-extreme learning machine. International Transactions on Electrical Energy Systems, 2018. **28**(4): p. e2519.
29. Hajian, M. and A.A. Foroud, A new hybrid pattern recognition scheme for automatic discrimination of power quality disturbances. Measurement, 2014. **51**: p. 265-280.
30. Upadhyaya, S., S. Mohanty, and C. Bhende, Hybrid methods for fast detection and characterization of power quality disturbances. Journal of Control, Automation and Electrical Systems, 2015. **26**(5): p. 556-566.

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