Pattern Recognition of Time-Varying Signals Using Ensemble Classifiers

M. Venkata Subbarao, Sudheer Kumar Terlapu, V. V. S. S. S. Chakravarthy, and Suresh Chandra Satapaty

Abstract A new classification approach for time-varying power quality (PQ) signals using ensemble classifiers (EC) is proposed in this paper. To achieve high performance, existing expert systems require several signal features so that these systems have more computational complexity. In order to reduce the computational cost and to improve the accuracy further, a new set of features called moments and cumulants are introduced in this paper to classify PQ events. Further, the performance of various ensemble classifiers is analyzed with the proposed feature set. Moreover, the analysis is carried out with different training and testing rates. Finally, the performance comparison is made with that of the existing techniques to prove the superiority of the proposed features and classifiers.

Keywords PQ signals · Ensemble classifiers · Moments and cumulants · Boosting · Bagging

1 Introduction

The exploitation of sensitive electronic components in applications of smart cities, smart buildings, and homes is growing exponentially [1]. These sensitive devices are easily affected by PQ disturbances, such as sags, surges, interruptions. [2, 3]. In real-time applications, failure of these sensitive devices may cause serious damage, especially in smart applications [4]. An automatic or blind recognition system is required to detect and identify the occurrence of PQ problem, so that devices can be

M. V. Subbarao (✉) · S. K. Terlapu
Department of Electronics and Communication Engineering, Shri Vishnu Engineering College for Women, Bhimavaram, India
e-mail: mandava.decs@gmail.com

V. V. S. S. S. Chakravarthy
Department of Electronics and Communication Engineering, Raghu Institute of Technology, Visakhapatnam, India

S. C. Satapaty
Department of Computer Science and Engineering, KIIT, Bhubaneswar, India

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prevented from damage [5]. In the last two decades, the researchers have developed different classification methods such as rough set-based [6], discrete wavelet-based [7, 8], neural network-based S-transform and modified ST-based [9–12], etc., for recognition of PQ events. Recently, artificial neural networks, rule-based expert systems, data mining-based classifiers, and fuzzy logic classification systems [13] are developed for classification of PQ events. All these methods extracted some specific features such as skewness, energy, mean, kurtosis, standard deviation, variance, and an average of the squared absolute values, etc., from the single and multiple disturbances for classification. Proper selection of features from the feature vector set is required to get more accuracy in classification and to reduce the classification time of the classifier. Some other approaches for classification of PQ events are discussed in Table 1.

To overcome the drawbacks of existing PQ classification approaches, a new attempt has been made in this present work to develop efficient algorithms for PQ

Table 1 PQ classification approaches

Ref. no.	Feature extraction method	Classifier	Feature selection	Number of disturbances	Accuracy		Year
					30 dB	20 dB	
[16]	WT	DT	x	5	96	x	2018
[17]	VMD	DT	x	9	93.8	x	2015
[18]	VMD	DT	x	9	96.7	x	2018
[19]	FDST	DT	x	13	x	98.3	2018
[20]	FDST	DT	x	11	95.3	x	2014
[21]	ST	DT	x	11	97.9	x	2013
[22]	TT	DT	ACO	9	91.2	x	2011
[22]	TT	DT	PSO	9	95.6	x	2010
[23]	DWT	SVM	x	5	98	95.6	2009
[24]	DWT	SVM	x	9	97	96.3	2011
[25]	WPT	SVM	x	8	93.4	x	2002
[26]	WPT	SVM	GA-FKNN	8	96.2	x	2012
[27]	DWT + HST	SVM	Gram-Schmidt orthogonal transform	10	99.3	98.7	2014
[28]	DWT + HST	SVM	Mutual forward selection	8	99.2	98.4	2014
[19]	FDST	Quadratic SVM	x	13	x	94.1	2018
[29]	VMD	SVM	x	6	x	x	2015
[30]	TQWT	SVM	x	14	96.4	96.4	2018

event classification. In order to develop the new algorithms, the following assumptions are considered. First, the classifier needs to be accurate. The accuracy is measured by the true-positive rate and false-negative rate. The lower false-negative rate gives better classifier for PQ classification. Second, the PQ event classifier needs to be robust under various noisy conditions. Third, the classifier is required to meet the essential requirements such as better classification accuracy even with more number of PQ classes in the pool.

The rest of the paper is organized as follows. Section 2 gives about the system model and feature extraction. Proposed EC is discussed in Sect. 3. In Sect. 4, the performance of the proposed EC is evaluated for different PQ signals. Section 5 concludes the article.

2 System Model

The proposed framework for PQ signal recognition is shown in Fig. 1. It involves feature extraction and training followed by testing.

Training of the classifier is performed with the extracted features. Finally, recognition is done with the trained EC.

The moments of a time-varying signal $y(k)$ are given by

$$M_{pq} = E\left[y(k)^{p-q} y^*(k)^q\right] \tag{1}$$

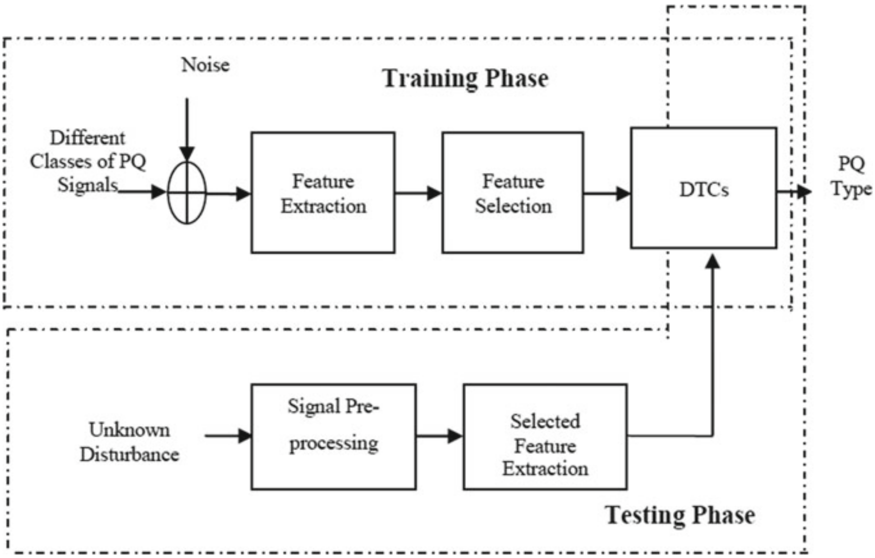

Fig. 1 PQ recognition framework

where p is the order of moment.

These moments are further used to derive the multi-order cumulants as follows:

$$C_{20} = E\left[y^2(k)\right] \tag{2}$$

$$C_{40} = M_{40} - 3M_{20}^2 \tag{3}$$

$$C_{60} = M_{60} + 30M_{20}^3 - 15M_{20}M_{40} \tag{4}$$

Here, C_{20}, C_{40} and C_{60} are second-, fourth-, and sixth-order cumulants, respectively.

3 Ensemble Classifier

The prediction accuracy of various PR classifiers is differed across data sets due to the algorithmic variability of the classifiers. It is not possible to predict the best working classification algorithm for different data sets. To overcome this problem, proposed ensemble classifiers are constructed with a set of different classifiers in order to allow them to vote for decision making. Through majority vote, these classifiers provide the best prediction accuracy. Ensemble classification is a nonlinear ML approach. An EC contains a set of autonomously trained classifiers, and their predictions are collected when recognizing new object. Finally, based on their majority vote, prediction will be done.

The most widely used ensemble technique is called boosting [14], and it works with the weighted training set. Once boosting is completed, then ensemble classifier model is ready for testing. In the testing phase, the unknown testing data is applied to ensemble model for PQ prediction. The detailed process using ensemble classifier is shown in Fig. 2 [15].

In this section, five types of ensemble classifiers such as bagged tress (BaT), boosted trees (BoT), subspace discriminant KNN (SDKNN), subspace KNN (SKNN), and RusBoosted trees (RBT) are developed for PQ recognition in combination with features listed in the Sect. 2. Bagged and boosted trees are constructed from deep trees, and these are slower in speed, whereas, subspace KNN and subspace discriminant KNN uses discriminant analysis and KNNs. In RusBoosted trees, weak learners will be boosted based on random under-sampling.

4 Results and Discussions

The recognition accuracy of proposed ECs is analyzed with seven types of PQ signals which are listed in Table 3. The detailed simulation parameters are discussed in

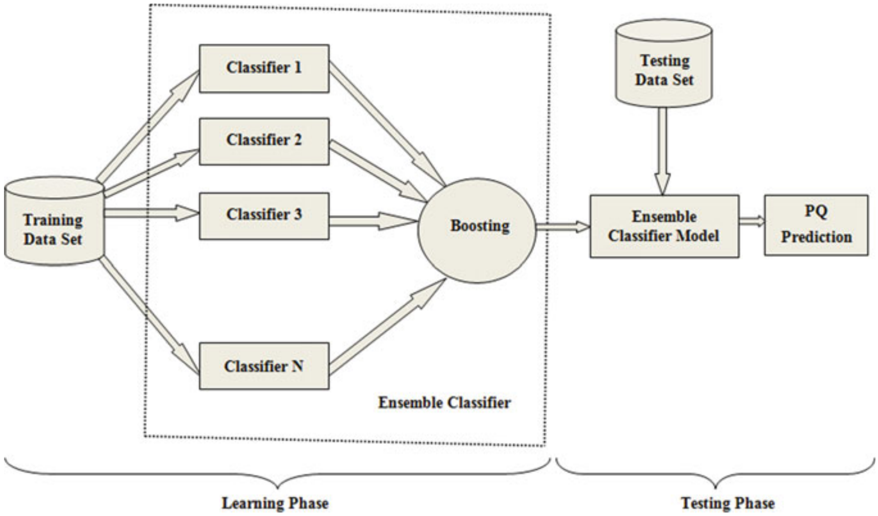

Fig. 2 PQ recognition with EC

Table 2. For the experiments, each PQ disturbance is considered for 1000 times at different SNR values. A set of features C_{20}, C_{40} and C_{60} are extracted from each copy signal and are used for training and testing. The accuracy of proposed ECs is tested at 50–90% training and 50–40% testing.

Table 3 shows the numerical values of the three selected features for all classes of PQ disturbances which are considered for simulation. These selected features are used for training the proposed ECs where LB and UB are lower bound and upper bound, respectively.

The performance of the proposed ECs with various percentages of training set is shown in Table 4. Among all the proposed classifiers, BaT and BoT classifiers have superior performance.

The recognition accuracy comparison of proposed ECs with various existing methods is shown in Table 5. From Table 5, it is proved that, the proposed EC classifiers

Table 2 Simulation parameters

Parameter	Description
PQ signals	Momentary interruption, sag, flicker, spikes, harmonics, swell, transient
Size of data set	7000*3 (1000 copies of each PQ class under varying noise conditions, 3 statistical features)
Size of training set	50–90%
Size of testing set	10–50%
Performance indices	Accuracy
Classifiers	BaT, BoT, SDKNN, SKNN, and RBT

Table 3 Cumulants of PQ events

Label	PQ signal	Features					
		C_{60}		C_{40}		C_{20}	
		LB	UB	LB	UB	LB	UB
S1	Sag	8.30	9.20	−1.42	−1.32	0.00	0.39
S2	Swell	9.37	9.51	−1.45	−1.43	0.03	0.10
S3	Outage	2.60	2.81	−0.83	−0.81	0.04	0.14
S4	Transient	65.7	71.0	5.30	5.50	0.02	0.07
S5	Flicker	6.90	7.18	−1.24	−1.21	0.03	0.14
S6	Harmonics	7.60	7.86	−1.30	−1.28	0.03	0.12
S7	Spikes	9.50	9.67	−1.46	−1.44	0.02	0.10

achieved the optimal classification accuracy even with less training. The recognition capability of proposed ECs is superior to that of existing approaches. The training time of proposed ECs is also very less.

5 Conclusion

A new PQ recognition approach using ensemble classifiers is proposed in this paper. Three new PQ signal features C_{20}, C_{40} and C_{60} are used along with the ensemble classifiers for PQ signal classification. Further, the recognition performance of proposed ECs is analyzed at various training and testing rates. From the experiments, it is clear that the performance of proposed ECs is superior to that of the existing techniques. Further, the research can be extended by incorporating optimization algorithms along with the proposed pattern recognition algorithms to improve classification accuracy and to reduce the training time.

Table 4 Performance of proposed ECs

Classifier/ % of training	% of recognition accuracy								
	90	85	80	75	70	65	60	55	50
BaT	100	100	100	100	100	99.9	99.9	99.9	99.9
BoT	100	100	100	100	100	99.9	99.9	99.8	99.8
RBT	100	100	100	99.9	99.9	99.8	99.8	99.8	99.8
SDKNN	100	100	99.8	99.8	99.6	99.5	99.1	98.9	98.9
SKNN	99.8	99.8	99.7	99.6	99.6	99.5	98.9	98.8	98.8

Table 5 Performance comparison of different methods

Method	Number of features	Training time (sec)	Accuracy (%)
ST, fuzzy C-means and APSO [13]	8	–	96.33
ST, fuzzy C-means and GA [13]	8	–	96.45
ST and PNN [11]	7	–	96.10
WPT and ANN [12]	7	31.26	95.25
ST and PNN [10]	3 4	0.9 (CPU)	95.91 97.40
DWT [2]	8	–	97.81
WPT and SVM [12]	7	27.68	97.25
Proposed BaT Training with $\geq$ 70% Training with 50–65%	3	2.21–2.39	100 99.9
Proposed BoT Training with $\geq$ 70% Training with 60–65% Training with 50–55%	3	2.19–2.41	100 99.9 99.8

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