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New automated power quality recognition system for online/offline monitoring

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ABSTRACT

One of the most important issues in the PQ assessment is diagnosis of Power Quality Disturbances (PQDs) using an effectual low computational burden strategy. We recommend a new approach for PQ analysis that addresses several major problems of prior works, including algorithm execution time, computational complexity, and accuracy. This paper suggests an effective and comprehensive method, so-called "integrated approach", for extracting features using integration of discrete wavelet transform and hyperbolic S transform. Moreover, a comparative assessment of PQDs recognition using various combinations of different Feature Selection (FS) and classification methods is presented. FS can reduce the dimension of feature space which leads to better performance of detection system. Four well-known FS techniques namely modified relief, mutual information, sequential forward selection, sequential backward selection and three benchmark classifiers, are considered. The particle swarm optimization is used to obtain optimal parameters of these classifiers. The key attribute of this paper is that it yields good time–frequency resolution with low computation burden for optimal PQ monitoring structure. Empirical results show that the proposed structures can yield an automatic online/offline monitoring of PQ with sparser structures and less computational execution time, both in the training and recognition phases, without sacrificing generality of performance.

1. Introduction

The increasing use of tools sensitive to power system disturbances and the deal with financial aspects have increased the awareness of PQ problems and created a need for widespread automatic monitoring of the power system operation [1]. To avoid improper operation of electronic devices due to effects of the PQDs, the protection systems have been equipped with microprocessors that provide integrated multifunctions and response very quickly. Moreover, they can send PQD information to central monitoring station for offline analysis. Offline PQDs recognition endures from drawback of imprecision and increased risk when power system operating point changes from the nominal value [2]. In the future, this facility will develop the online monitoring of PQ and provide numerical analysis of available PQ data [2,3]. Previous researches in PQDs identification pay less concentration to realtime applications which require low cost in memory and execution time but no loss in accuracy. In online PQ monitoring, huge computational burden is needed to overcome the complexity of methods due to large input vector. Hence, fast processor and much

E-mail addresses: Mehdi.hajian.sem@gmail.com (M. Hajian), aakbari@semnan.ac.ir, akbari_asghar@yahoo.com (A. Akbari Foroud), abdoos_a@yahoo.com (A.A. Abdoos). memory space must be provided which may be expensive and sometimes may not be applicable [4]. For the online classification of PQDs, the emphasis is on decreasing of required computational burden of recognition scheme [2]. In this paper, a new and suitable structure for online detection and classification of various types of PQDs is described. Also, the appropriate structure for offline recognition PQDs is proposed.

Today, researchers are trying to present new detection scheme with high accuracy detection [1,4–7]. In spite of large number of presented schemes in the field of PQ monitoring, a useful automated online robust monitoring system is still missing and the presented method in this paper is the main step in this field.

Recently, presented methods have been concentrated around pattern recognition schemes [1,2]. To have suitable features that reflect the main attribute of disturbance waveform, different types of extracted features must be examined. In order to obtain a comprehensive feature space, the important features and different combinations of them must be considered. Therefore the dimension of PQ input is usually high. High dimensionality of feature vector has become a critical problem in practical pattern recognition applications. Input vectors with high dimension are usually redundant and may decrease the accuracy of pattern recognition schemes. A common way to solve these problems is to adopt dimensionality reduction methods. Many literatures try to present new methods for reduction of the high dimensional feature space





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Abbreviationsra parameter which controls the position of the Gaussian windowPQDspower quality disturbancestDWTdiscrete wavelet transform φ^2_{ly} HSThyperbolic S-transform φ^2_{ly} HSThyperbolic S-transformZa modified relief γ^2_{HY} MMutual informationSFSsequential forward selectionSBSsequential backward selectionMWnull sequenceMSVMmultisupport vector machinesPNNprobabilistic neural networkPSOparticle swarm optimizationPSOparticle swarm optimizationPSOparticle swarm optimizationFTtime-frequencyTFtime-frequencyTFAtime-frequency<	List of abbreviations and symbols <i>f</i>		f	frequency
PQDspower quality disturbancesttimePQDspower quality disturbances V a scalable Gaussian windowDWTdiscrete wavelet transform φ_{hy}^2 hyperbolic window parameterHSThyperbolic S-transform Z a hyperbola in $(-\tau)$ FSfeature selection γ_{HY}^B backward-taper parameterRmodified relief γ_{HY}^B forward-taper parameterMMutual information $W(m, n)$ the Fourier transform of the hyperbolic windowSFSsequential backward selection $W(m, n)$ the Fourier transform of the hyperbolic windowRmodified relief γ_{HY}^B backward-taper parameterMMutual information $W(m, n)$ the Fourier transform of the hyperbolic windowSBSsequential backward selection φ the mother waveletMSVMmultisupport vector machines r the scaling parameterPNNprobabilistic neural network s the translating parameterK-NNK nearest neighbor $\nu(k)$ the sampled signalPSOparticle swarm optimization $H(X,Y)$ the entropy of two discrete random variables X and YTFTshort time Fourier transform $H(X/Y)$ the conditional entropy of X regarding YFmAfrequency-maximum amplitude $H(X/Y)$ the conditional entropy of X regarding YMRAmulti-resolution analysis $MI(X, Y)$ the value of the mutual information (M)QMFquadrature mirror filters $nh_k(s_m)$ nearest hit of orde			τ	
PQDspower quality disturbancesWa scalable Gaussian windowDWTdiscrete wavelet transform φ_{hy}^2 hyperbolic window parameterHSThyperbolic S-transformZa hyperbolic window parameterFSfeature selection Z^B backward-taper parameterRmodified relief T_{HY}^B backward-taper parameterMMutual information $W(m, n)$ the Fourier transform of the hyperbolic windowSFSsequential forward selection $W(m, n)$ the frequency shifted discrete Fourier transformSBSsequential backward selection φ the mother waveletMSVMmultisupport vector machines r the scaling parameterPNNprobabilistic neural network s the translating parameterK-NN K nearest neighbor $\nu(k)$ the sampled signalPSOparticle swarm optimization $H(X, Y)$ the entropy of two discrete random variables X and YTFtime-maximum amplitude $P(X Y)$ the conditional entropy of X regarding YTFAfrequency-maximum amplitude $P(X Y)$ the value of the mutual information (M)QMFquadrature mirror filters $nh_k(s_m)$ nearest hits of order k for sample S _m Symbols x_{ix,x_j} the kernel function dim_{total} Soutput matrix of S-transformdim.the feature dimension at the ith trial	ADDIEVIL	itions		Gaussian window
TFtime-frequency $P(X,Y)$ the initial probability distribution of two discrete random variables X and YTmAtime-maximum amplitude $H(X/Y)$ the conditional entropy of X regarding YFmAfrequency-maximum amplitude $P(X Y)$ the posterior probabilities of X given YMRAmulti-resolution analysis $MI(X,Y)$ the value of the mutual information (M)QMFquadrature mirror filters $nh_k(s_m)$ nearest hit of order k for sample S_m Symbols $k(x_i, x_j)$ the kernel functionSoutput matrix of S-transformdim _i	PQDs DWT HST FS <i>R</i> M SFS SBS MSVM PNN <i>K</i> -NN PSO	power quality disturbances discrete wavelet transform hyperbolic S-transform feature selection modified relief Mutual information sequential forward selection sequential backward selection multisupport vector machines probabilistic neural network <i>K</i> nearest neighbor particle swarm optimization	W φ^{2}_{hy} Z γ^{B}_{HY} γ^{F}_{HY} $W(m, n)$ $H(m, n)$ φ r s $\nu(k)$ $H(X, Y)$	time a scalable Gaussian window hyperbolic window parameter a hyperbola in $(\tau-t)$ backward-taper parameter forward-taper parameter the Fourier transform of the hyperbolic window the frequency shifted discrete Fourier transform the mother wavelet the scaling parameter the translating parameter the translating parameter the sampled signal the entropy of two discrete random variables <i>X</i> and <i>Y</i>
FmAfrequency-maximum amplitude $H(X Y)$ the control of the posterior probabilities of X given YMRAmulti-resolution analysis $P(X Y)$ the posterior probabilities of X given YQMFquadrature mirror filters $MI(X, Y)$ the value of the mutual information (M) $nh_k(s_m)$ nearest hit of order k for sample S_m Symbols $k(x_i, x_j)$ the kernel functionSoutput matrix of S-transformdim _i	TF	time–frequency	P(X,Y)	
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Symbols $k(x_i, x_j)$ the kernel functionSoutput matrix of S-transform im_{total} the total feature dimensionthe feature dimension at the <i>i</i> th trial			$nh_k(s_m)$	nearest hit of order k for sample S_m
S output matrix of S-transform \dim_i the feature dimension at the <i>i</i> th trial	Symbols		$k(x_i, x_j)$	the kernel function
	S	output matrix of S-transform	corui	
	h		R _i	the average recognition rate achieved at the <i>i</i> th trial

[8]. Since, PO monitoring systems must analyses and save huge data amount, robust data mining techniques must be applied to obtain an optimal PQ analyzer. Traditional methods for classification of PQDs include two major stages that comprise a pattern recognition process: feature extraction and classification [1]. Data reduction is performed via FS in our approach. FS has become the focus of many real-world application leaning expansions and applied research in recent years. In recent years, FS has been widely used in pattern recognition systems due to its important impact on classifiers performance [9]. FS can be generally categorized into three main approaches: filter, wrapper, and hybrid approaches [5]. The filter approach requires the arithmetical analysis of the feature set only for resolving the FS duty without utilizing any classifying model. The wrapper approach engages with the prearranged learning form, selects features on evaluating the classification accuracy of the particular learning form [10]. The hybrid approach attempts to take advantage of the filter and wrapper approaches which permits the latter to utilize the information delivered by the filter algorithm in order to accelerate the convergence of the wrapper algorithm [11]. The proposed methodology of this paper is executed via three serial stages shown in Fig. 1.

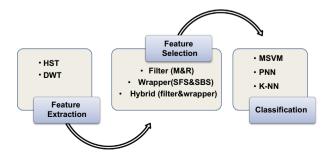


Fig. 1. Configuration of the proposed monitoring process.

Generally. Feature extraction and feature selection are essential stages in order to enhance a pattern recognition system as preanalysis data to determine the most important features. The first stage towards automatic analysis and data monitoring is the socalled feature extraction. In this subsystem some useful features are extracted based on two powerful time-frequency analysis tools i.e. Discrete Wavelet Transform (DWT) and Hyperbolic S Transform (HST). In this paper, we apply a challenged feature selection stage for reduction of required data and increasing the interpretability of features for classifiers. This main stage has been neglected in the most researches in the field of recognition of PO events. In the FS stage, most important features from whole extracted features in the first step are selected using wrapper and filter and proposed hybrid methods. Less important features are removed from training feature vectors. Third stage is the classification. In this stage, selected features obtained from preprocessing stages (i.e. feature extraction and feature selection stages) are used for training of three well-known classifiers i.e. MultiSupport Vector Machines (MSVM), Probabilistic Neural Network (PNN) and K Nearest Neighbor (K-NN). In order to find the best accuracy for detection of PQDs, obtained results of these three classifiers are compared.

2. The proposed framework

In the literature, most of the PQ assessment works are based on offline analysis of the monitored data instead of online processing of the captured information. Therefore, online analysis is an important consideration for power utilities and their customers in order that diagnosis and alleviation effect of PQDs can be implemented quickly [2]. To achieve this, there is a need for powerful software tools that can perform PQD analysis automatically, low complexity, efficiently, versatility and accurately [12]. With the purpose of obtaining a comprehensive feature space, the Download English Version:

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