Wavelet Based Detection and Classification Power Quality Disturbance using SVM and PSO

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Abstract: This paper introduces a novel approach to detect and classify power quality disturbance in the power system using Support Vector Machine (SVM). The proposed method requires less number of features as compared to conventional approach for the identification. For the classification, 8 types of disturbances are taken in to account. The classification performance of SVM is compared with Radial basis Function neural network (RBNN).The classification accuracy of the SVM network is improved, just by rewriting the weights and updating the weights with the help of cognitive as well as the social behaviour of particles along with fitness value by using Particle Swarm Optimization (PSO). The simulation results possess significant improvement over existing methods in signal detection and classification with lesser number of features

Keywords: Support Vector Machine, Radial Basis function Neural Networks, Wavelet Transformation, Power Quality and Particle Swarm Optimization

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1. Introduction

The quality of electric power is more important because one of the main problem the industries facing is the distortion in electrical supply. The disturbance such as voltage sag, swell with and without harmonics, momentary interruption, harmonic distortion, notch, flicker, spike and transients causing problems such as malfunction, instability, short life times, failure of electrical equipment and so on. Switching off of large load and energization of large capacitor may cause voltage swell. Whereas the faults leading to voltage sag or momentary interruption, harmonic distortion and notching in the voltage and current are caused because of the usage of solid state switching device and nonlinear power electronically switched loads such as rectifier or inverters. Transformer energization or capacitor switching may cause transients. Flicker is caused because of furnaces and lightning strikes may lead to spikes.

In power system, these disturbances need to be identified in order to improve the power quality. PQ events identification is difficult because it involves wide range of disturbance categories. Therefore, the decision boundaries of disturbance features may overlap. For these reasons, the need of power quality analysis has been strongly increasing. Many techniques have been proposed in the literature to detect and classify the events envelope. Traditionally, probabilistic approach has been used for time varying signals in a power quality analysis, assuming that the power line disturbance components vary too slowly to affect the accuracy of analytical process (Ibrahim W.R.A and M.M.Marcos, 2002).Another work suggested a combination of spectral method with probabilistic approach, which referred as evolutionary spectrum (Gu .Y.H and M.H.J.Bollen, 2002).The Discrete Fourier Transforms (DFT), which is computed via the Fast Fourier Transforms (FFT), is used to extract the features in the waveforms. However, the accuracy of the DFT algorithm is affected by the product available in the voltage waveform. Further, pit falls of the DFT are discussed in (Gorgom et al., 2005), which describes the digital filtering of the signals. Transient characteristics of disturbances waveforms are discussed in (Panigrahi.B.K and V.R.Pandi,2009). Since they pertain to signal analysis . This analytic technique includes the Short-Time Fourier Transform (STFT) which briefs time – frequency information related to disturbance waveforms. However, the disturbances signal cannot be adequately described in this transform, due to fixed window size (Chun-

Yao Lee and Yi-Xng shen.2011).For this reason, S-Transform (ST) is often adopted as a tool for signal analysis. The superior properties of the ST are that the modulating sinusoidal is fixed with respect to the time axis, while the localizing scalable Gaussian window dilates and translates. As a result, the phase spectrum is absolute in the sense that it always referred to the origin of the time axis, the fixed reference point. ST is found to be superior (Edward reid, 1996). However, the computational time is very large compared to Wavelet Transform (WT), which is undesirable for on-line applications. WT based approach, such as Wavelet MRA, has been widely applied to solve these issues (Mallat.S.G, 1989).

Wavelet Transform and multi-resolution analysis provide a short window for high frequency components and long window for low frequency components (McConaghy et al.,2003) and hence, provides an excellent time frequency resolution(Chia-Hung Lina and chia-Hao Wang,2006).This allows WT for analysis of signals with localized disturbances components and also for classifying low and high frequency power quality problems. Using the properties of WT technique and the feature of the decomposed waveforms along with ANN algorithm, it is possible to extract important information from a disturbance signal and determine the type of disturbance that caused (Inigo Monedero et al., 2007). The energy of the distorted signal will be partitioned at different resolution levels in different ways depending on the events available (Masoum et al., 2010). The standard deviation can be considered as a measure of energy signal with zero mean (Gaing, 2004).

The classification of seven types of PQ disturbances with self-organizing learning array system considering 11 features, besides 22 families of wavelet are tested to identify the best one for a better classification . Classification of eleven types of PQ events using wavelets and Probabilistic Neural Network (PNN) is discussed (Mishra et al.,2008), Energy distribution at 13 decomposition levels of wavelet and time duration of each disturbance are taken as features and applied to PNN for classification. If large number of features is considered, it may result in high memory and computational overhead. Further, eleven types of PQ events are also classified with the help of ST and PNN using only four-dimensional feature sets for training and testing. The computation time is very large compared to WT.

Considering all these issues related to detection and classification of PQ events, Support Vector Machine (SVM) classifier based on wavelet transform is proposed in this paper. Support vector machines which are relatively recent development belongs to a family of generalized linear classifier (Cristiani,N and Shawe J.taylor, 2000). SVM maximize predictive and classifying accuracy using machine learning theory. SVM has strong statistical learning theory which minimize the probability of misclassification of unseen patterns with an unknown probability distribution of data. SVM overcomes the real world problem often requires hypothesis space which are more complex. SVM performs better than other networks in terms of generalization and find non-linear boundaries for linearly non-separable classes (Dwivedi et al.,2008).The major advantage of SVM is that if new types of disturbances are added to the classifier means it is straight forward to extend the system. Here, less number of features is required for effective classification of 8 types of PQ events accordingly. The SVM provides accurate results even with inputs found out under high noisy conditions. Thus, the proposed method provides robust and accurate results for power quality events classification.

The performance of SVM is compared with other well-known RBFNN. The classification accuracy of the SVM is improved, just by rewriting the weights and updating the weights with the help of cognitive as well as the social behaviour of particles along with a fitness value by particle swarm optimization (PSO) algorithm. PSO can be a solution which models the cognitive as well as the social behaviour of a flock of birds which are in search of food over an area (R.C.Eberhart and Y.Shi, 2001).It improves neural network in various aspects such as learning algorithm, network connection weight and architecture .

Here, less number of features is required for effective classification of 8 types of PQ events.

The SVM-PSO provides accurate results even with inputs found out under high noisy conditions. The performance of SVM-PSO is compared with RBFNN, to prove the stability and accuracy of the classification. The proposed method is tested with the inclusion of white noise in the signal. From the simulation results, it is found that SVM-PSO classifies the PQ event more effectively than other well-known algorithms.

To summarize, the paper shows the power quality problems classification using WT and SVM-PSO. First the work handles with wavelet transformation and feature extraction from WT needed by the neural networks for training and for effective classification for all the 8 types. Next the paper describes the structure and results and discussion about detection and classification PQ events using SVM and similarly for SVM-PSO. Finally, the performance of SVM-PSO is evaluated by simulation and compared with other considered approach.

2. Wavelet Transforms

Wavelet transformation has the ability to analyse different power quality disturbances in both time and frequency domain. The wavelet transform is useful in extracting features of various power quality disturbances. Wavelet analysis deals with expansion of function in terms of a set of basis function. However, wavelet analysis expands functions not in terms of trigonometric polynomials but in terms of wavelets. Moreover, another important property that the wavelet possesses is perfect reconstruction, which is the process of reassembling a decomposed signal or image into its original form without loss of information.

2.1 Multi-resolution analysis

Scaling function and wavelet function are used as a building block to decompose and construct the signal at different resolution levels in Multi-Resolution Analysis (MRA).Representation of signals at various levels of resolution is the ultimate goal of MRA.MRA consists of two filters in each level and they are low pass and high pass filters. The resolution of the signal, which is a measure of the amount of detail information in the signal, is changed by the filtering operations, and the scale is changed by up-sampling and down-sampling operations. Down-sampling, a signal corresponds to reduction of the sampling rate, or removing some of the samples of the signal. On the other hand, up-sampling a signal corresponds to rising of the sampling rate of a signal by adding new samples to the signal. MRA decomposition and reconstruction are shown in Fig.1.(a) and (b).

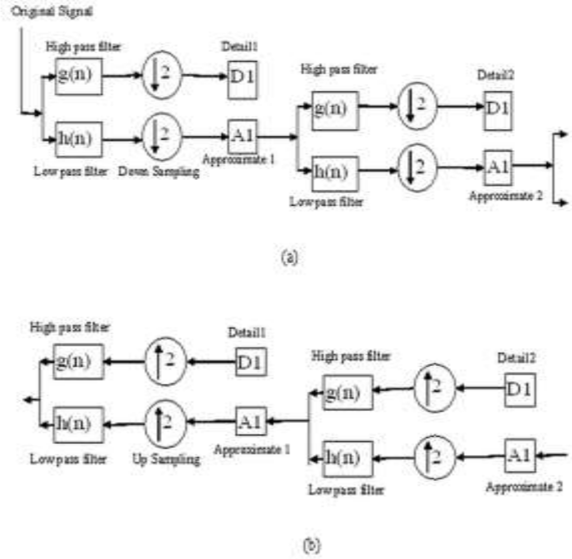

Figure.1:(a) Multiresolution analysis decomposition and (b) Reconstruction.

Assume a signal *x[n]*, discrete time signal is distributed in 2 level. This signal is filtered into high frequency component in level 1 by using high pass filter (*g(n))* and low frequency components in level 2 by using low pass filter *(h(n))*. This signal is passed through down sampling in MRA level 2.The components in level 1 are used as initial signals. These signals are passed through high-pass filter and low-pass filter. The outputs of filter can be mathematically expressed as in equation (1) and (2) as follows (Kanirajan, P & Suresh Kumar, V (2015).

$$y1[k] = \sum_n x[n].g[2k-n] \qquad (1)$$

$$y2[k] = \sum_n x[n].h[2k-n] \qquad (2)$$

Where *g(n)* is high pass filter.

h(n) is low-pass filter.
Where *y1 [k]* and *y2 [k]* are the outputs of the high-pass and low-pass filters, respectively.

2.2 Wavelet Based Feature Extraction

Power system comprises of various kinds of electrical disturbances such as sag, swell, momentary interruption, voltage fluctuation, harmonics etc. and for the analysis they are generated using MATLAB code. The generated waveform shows the plot of amplitude of a given magnitude in the time frequency coordinates system for the following signals and shown in figure 2 (a) - 2(h). Which all are decomposed by wavelet to extract features with the appropriate selection of the wavelet and decomposition scale.

S1-Normal, S2-Pure Sag, S3 Pure swell, S4-Momentary interruption, S5-Voltage fluctuation, S6- Harmonics, S7- Transients and S8- Sag with fluctuation, momentary interruption, swell and harmonics (Kanirajan , P & Suresh Kumar, V (2015).

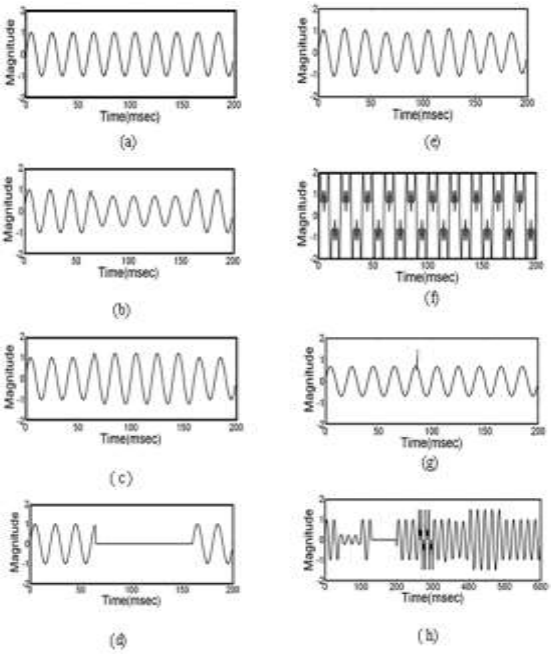

Figure .2: (a) Normal Signal, (b) Pure Sag, (c) Pure Swell,(d) Momentary Interruption , (e) Voltage Fluctuation, (f) Harmonics, (g) Transients (h) Sag with Fluctuation, Momentary Interruption, Swell and Harmonics.

2.3 Selection of Wavelets and Decomposition Scale

In this section, a simple yet effective method to detect and classify power quality disturbance, there are a number of basis functions that can be used for wavelet transformation. The wavelet functions used in the transformation are through translation and scaling, it determines the characteristics of the resulting wavelet transform. Therefore, the details of the particular application should be taken in to account and the appropriate wavelet function should be chosen in order to use the wavelet transform effectively. The wavelets are chosen based on their shape and their ability to analyze the signal in a particular application. So the best wavelet function and optimal decomposition scale need to be carefully selected. Wavelet energy is the index to reflect the energy concentration of wavelet coefficients on certain scales.

The larger the wavelet energy, the more the information is preserved after decomposition.

The definition of total energy and average power for a signal *x[n]* being expressed as follows in equation (3)-(5).

$$E = \sum_{n=-\infty}^{\infty} x^2[n] \qquad (3)$$

And the average power is

$$P = \lim_{x \to \infty} \frac{1}{2N} \sum_{n=-N}^{N} x^n[n] \qquad (4)$$

And for a periodic signal of fundamental

period *N*, the average power is given by

$$P = \frac{1}{N} \sum_{n=-0}^{N-1} x^2[n] \qquad (5)$$

In this Daubechies (Db) and Symlet wavelets are taken for the further analysis. The daubechies wavelets are a family of orthogonal wavelet defining a discrete wavelet transform, characterized by a maximal number of vanishing moments and given support to each wavelet, and there is a scaling function which generates an orthogonal multi-resolution analysis. The symlets are nearly symmetrical wavelets proposed by daubechies as modification to the Db family, and the properties of these two wavelet families are similar. These wavelets have been chosen because they have shown best performance in analysing disturbance signals. The wavelet corresponding to the highest total wavelet energy is chosen as the best wavelet function, and the scale corresponding to the highest wavelet energy is chosen as the optimal decomposition scale.

All the proposed disturbance were taken in this paper and results are listed in Table 1 and Table 2, the elements shaded indicates the highest wavelet energy of a specific signal, corresponding to a certain wavelet functions. Among these Db4 seem to have highest wavelet energy levels, and chosen as the best wavelet for feature extraction.

Table 1: Results of Selection of Wavelet Function

Events	Daubechies				Symlets			
	Level				Level			
	2	3	4	5	2	3	4	5
S1	0.9907	0.9826	0.9921	0.9899	0.9819	0.9717	0.9846	0.9837
S2	0.9748	0.9601	0.9863	0.9726	0.8915	0.9256	0.9793	0.9614
S3	0.8417	0.8462	0.8917	0.8733	0.8367	0.8511	0.8845	0.8815
S4	0.8342	0.8172	0.8915	0.8678	0.7942	0.8173	0.8591	0.8498
S5	0.6925	0.7692	0.7647	0.7413	0.7641	0.7612	0.7949	0.7817
S6	0.8569	0.8701	0.8724	0.8655	0.8602	0.8643	0.8597	0.8613
S7	0.8941	0.9118	0.9218	0.9197	0.8762	0.8771	0.8924	0.8891
S8	0.8974	0.9124	0.9479	0.9316	0.8862	0.8976	0.9062	0.9147

Table 2 : Results of Selection of Scale

Events	Daubechies					
	Scale					
	1	2	3	4	5	6
S1	0.3442	0.3639	0.4171	0.4987	0.5074	0.4982
S2	0.3911	0.3948	0.4794	0.5217	0.5737	0.4955
S3	0.3841	0.3979	0.4288	0.4812	0.4919	0.4871
S4	0.04681	0.0517	0.0594	0.0634	0.0678	0.0646
S5	0.0824	0.0961	0.0981	0.1211	0.1279	0.1245
S6	0.0724	0.0842	0.0849	0.1917	0.1981	0.1895
S7	0.2941	0.2974	0.2987	0.3156	0.3417	0.3196
S8	0.2926	0.2968	0.3014	0.3096	0.3406	0.3218

In Table 2 shows signal decomposition by Db4 in to scales and it is evident that the wavelet energy at scale 5 is the highest and can be used as the optimal decomposition scale for MRA.

The parameters of voltage waveforms during power quality events are statistically different from those that are calculated during an event free time period.

In this paper, features based on mean, standard deviation, Norm Entropy and Skewness of transformed signals are extracted and energy at each decomposition level, which has the ability to quantify the magnitude of variation within the signal, is also extracted. The extracted features help to distinguish one disturbance event from another. In order to extract feature of these signals, the standard deviation of power quality problem signal is subtracted from standard deviation of pure sinusoidal waveforms in case of analysis based on standard deviation multi-resolution analysis. In order to reduce the features dimension, the detail and approximate information for future training and testing will not be used directly. Instead, energy at each decomposition level is used as a new input variable for accurate and faster classification. In this way, the wavelet based feature extraction for future analysis has been constructed.

3. Support Vector Machine

SVM aims at maximizing the margin between the separating hyperplane and the data and minimizing an upper bound of generalization errors. Normally classification of data is done by determining a set of support vectors, which are members of the set of learning inputs that outlining hyperplane. SVM, uses structural risk minimization (SRM) principle which minimizes the generalization error on test sets.

The main aim of SRM is to choose less complex model for a given training sample and to map nonlinearly on to a high dimensional space so that the boundary will become linear in the new space to achieve better training class separation. The use of Kernels in the SVMs offers an alternative solution by nonlinearly projecting the input space in to high dimension space. The kernel function K (xi, x) the input vector and support xi drawn from the test data. In the SVM the optimal decision function constructed to predict and classify accurately the un seen data in to two classes and minimizes the classification error. This is achieved by SRM(V.N.Vapnik, 1998).The over fitting is mitigated because of good generalization ability of the resulting function by SVM and finds the large oriented hyperplane. MATLAB SVM toolbox is used to find the optimal separating hyperplane, which expressed mathematically in equation (6).

$$W^{*T}.x+b^*=0 \quad (6)$$

that maximizes the margin as well as minimizes the number of misclassified patterns.

The optimal weight vector W* is givens in equation (7).

$$W^* = \sum_{j=1}^{N} \lambda j^* \, xj^* \quad (7)$$

Where $\lambda 1^* = (\lambda 1^*, \lambda 2^*, \lambda 3^* \ldots\ldots\ldots\ldots \lambda N^*)$ is the solution of quadratic programming problem.

xi with $\lambda^* > 0$ are the support vector points. The classification of a new data vector x can be done with equation (8)

$$y=sign(f(x)) \quad (8)$$

Where, $f(x)$ is the optimal decision boundary deserved from the set of training samples which is expressed in equation (9).

$$f(x)=W^{*T}.x+b^* \quad (9)$$

The above equation can be expressed as shown in equation (10).

$$f(x) = \left(\sum_{j=1}^{n} \lambda \mathrm{j} * \ \mathrm{xj} \right) x + b * \quad (10)$$

Then with the dot product between the data and support vector the class $y \in \{-1,1\}$ of x is expressed in the training set. To decide the data a separating hyperplane may be used for a linear data. However, in practical the data is inseparable and nonlinear and there for to map this kernels are used (.Cristiani, N and Shawe J.taylor, 2000).The above construction can be extended to any type of separation.

4. Particle Swarm Optimization

Back-Propagation (BP) algorithm is a straightforward algorithm which is based on the steepest descent method. Backwards calculating weight does not seem to be biologically plausible. Neurons synaptic weight adjustment do not seem to work backward, and also in the design of SVM trained by BP algorithm, a set of system variables which affect voltage most, were selected as SVM inputs, if the range of (6) variation is increased, the accuracy of the voltage estimation greatly suffers. Furthermore, it suffers from extensive calculation and therefore in most of the cases has a slow convergence speed. Population based optimization tool is the PSO. To get the optimal solution, every single solution 'flies' over the solution space. To check how close they are optimal is evaluated by using a fitness function (R.C.Eberhart and Y.Shi, 2001) Kanirajan, P & Suresh Kumar, V (2015). Particles may have both cognitive and socialization. The neural network weight matrix is rewritten as an array to form a particle, and then initialized randomly and updated afterwards, according to the equation as (11) and (12).

$$w(t+1) = w(t) + \Delta w(t+1) \quad (11)$$

Δw(t+1)=w(t)+c_1.rand( ).[pBest (t)-w(t)]+c_2.rand( ).[gBest (t)- w(t)] (12)

Where w, c_1, c_2 is inertia, cognitive and social acceleration constant respectively.

pBest is the best solution that the particle has achieved and indicates the tendency to replicate their corresponding past behaviors. *gBest* is the best solution that has achieved so far by the specific particle in the whole population, which indicates the tendency to follow the success of others by the particles. Another important parameter is the maximum velocity *Vmax*, associated with PSO, which mainly determines the resolution with which the search space is searched. There may be chances to fly past the better solution by the particle if the value is very large and get trapped in the local optima if the value is small.

5. Results and Discussion

This section discusses the simulation of combined wavelet transformation with SVM for classification of 8 types of power quality problems. Here, mean, standard deviation, energy, Norm Entropy and Skewness are used as inputs to the SVM. Input signal for training is selected by random signal at a time. The training is set for learning rate 0.01 and target error 0.001. Each network is trained with 30 input data of each class and 100 data of each class are considered for testing. Weights are updated in each and every iteration after training the SVM in this way new training input is given to the network. The randomly selected signal from 100 signals of each power quality problem is used to test SVM. To evaluate the performance of SVM, their results are compared with the RBFNN. The classification result during testing is shown Table 6. The overall classification accuracy RBFNN and SVM is 96 % and 97.50% respectively. It is identified that SVM gives the better classification results for this case.

5.1 Comparison of Proposed Work with Real Time Data

In this section, to check the proposed networks potential, less number of events that is voltage sag, swell and under voltage and transients where used with 10 orientations, with different indices. The generated signals features were used for training and tested with practical data. To test the proposed work, data of (InigoMonedero *et al*.,2007) mainly for ideal signal (230 vrms and 50Hz),Sag with(40% and 20ms) , under voltage (40% and 1ms) and swell (20% and 60ms) were taken and then from them the features were extracted and given as input to the proposed trained SVM network. In similar way to test the potential of the proposed network the data of (Martin Valtierra-Rodrigues *at el* 2014) mainly transient and sag were are taken which is an experimental setup monitored at the point of common coupling, composed of a transformer bank in delta-wye of 350VA, a capacitor bank of 77 micro farad and two motors of 1 and 2hp (746W) respectively with data acquisition system with an low pass Butterworth antialiasing filter. The comparison results were shown in Table 3.

Table 3: Comparison of Proposed SVM with Others work Practical Data

Test Signals	**Disturbances**	**Classification rate %**	
		RBFNN	**SVM**
Simulated Signals using MATLAB	Sag	98	99
	Swell	93	98
	Under voltage	98	98
	Transients	96	97
InigoMonedero *et al*.,2007	Sag	98	98
	Swell	94	96
	Under voltage	97	98
	Transients	99	98
Martin Valtierra - Rodrigues *et al* 2014	Sag	98	98
	Transients	98	99

It is inferred that the proposed SVM network has the potential to deal with any data to produce better detection and classification rate, since it was trained with vast data with wide variations. Whereas 10 numbers of orientation may not be adequate in real cases for detection and classifications of PQ events.

5.2 Detection and Classification Using SVM-PSO

The PSO algorithm is different than any other technique, rather than training one network PSO trains a network of networks. It initializes all weights to random values and starts training each other, on each pass, PSO compare the networks fitness. Each network contains position and velocity. The position is related to weight and the velocity refers to updating of neural networks weights. Getting the best set of weight is the main function of PSO. In SVM implementation, the fitness value corresponds to a forward propagation and position vector corresponds to the weight vector. The best neighbour and global best are used to guide the particle new solution. Input variables are mean, standard deviation, energy, Norm Entropy and Skewness. To speed up the training, the variables are normalized. The function of PSO is to get the best set of weight. 80% of the generated inputs were used for training and remaining 20% were used for testing. For SVM-PSO with different initial weight, a population of networks was constructed and sum of square error in each iteration over the training data set were calculated and compared to find the best network in the neighbourhood .If minimum error required is achieved by the network means this weight is recorded for to use it for testing, otherwise again the algorithm is applied to get the best weight and updating of weight i.e position and velocity vector for each network .The overall accuracy of classification is the ratio of correctly classified events to that the of total number of events. The overall classification accuracy is 98.75 %.

5.3 Result and discussion based on Features

In any ANN approach, the main difficulty is that, if the number of input variables increases, ANN will take more time to train the network (Garcia-Perez, 2014). Hence, selection of features and number of features is necessary to any ANN approach for the real time problems. The performance of the network can be improved in terms of accuracy, time consumption by reducing the number of features. This work proposes Wavelet-MRA based feature selection technique. The input features are selected based on the values of mean, standard deviation, energy, Norm Entropy and Skewness of both detail and approximate coefficients of the signals. In different resolution levels, the energy of the wavelet coefficient varies. Energy of the low frequency signals and high frequency signals is distributed in approximation coefficients and in detail coefficients. Since, in real time the waveforms have higher frequency components, it is more desirable to use detailed coefficient energies. The performance of the proposed wavelet based on the feature selection method is compared based on the feature and number of features used for various classifier network Table 4.Shows the percentage of classification rate and central processing unit (CPU) time for training and testing. From the table it is inferred that network trained with less number of features give high classification rate with less CPU time for both training and testing, especially in SVM. So it is desirable to use less features to get better classification with less time which is very much need in real time online applications .

The performance of the proposed wavelet based feature selection method is compared with other works (S. Mishra et al 2008) , (Chun-Yao Lee and Yi-Xng shen.2011) and (Prakash K.Ray et al 2013) .The performance results were shown in Table 5.

Table 4: Comparison of Proposed SVM on Number of Features with Other Technique

Number of Features used	Features	Classifier	Classification rate %	CPU Time(sec) Training	CPU Time(sec) Testing
2	1.Energy 2. Standard Deviation	RBFNN	96.30	2	0.08
		SVM	97.85	1.2	0.07
3	1.Energy 2. Standard Deviation 3.Norm Entropy	RBFNN	95.85	3.2	0.38
		SVM	97.15	2.42	0.32
5	1.Mean 2.Energy 3. Standard Deviation 4.Norm Entropy 5Skewness	RBFNN	95.95	3.2	1.04
		SVM	96.85	3	0.95

Table 5: Comparison of Proposed SVM on Number of Features with Other Work

Features	Number of features used	Classifier	Classification rate %
Features Extracted using S-Transforms (S. Mishra *et a*l 2008)	4	PNN	97.4
	3	PNN	95.91
Feature Extracted using S-Transforms and T-Transformas (Chun-Yao Lee and Yi-Xng shen.2011)	5	APNN	96.3
		MLP	98.1
		K-NN	96.0
Features Extracted using S-Transforms (Prakash K.Ray *et al* 2013)	10	MPNN	96.66
		SVM	98.33
Features Extracted using Wavelet Transforms Proposed	2	SVM	97.30
		SVM-PSO	98.75

From the Table 4 and Table 5 it is inferred that the proposed wavelet based feature selection gives better classification rate with lesser number of features when compared with other works.

5.4 Detection and Classification performance under noisy condition

The inputs for training are noise free. However, the signals in the real system will always have noise. In order to test the robustness of SVM and SVM-PSO, the white noise, which has random normal distribution, is added to normal signal to test the performance of SVM-PSO under noisy environment. The signal to noise ratio (SNR) . 30 and 40 db were used for training and tested with 25, 30 and 40 db noise level. The test results are depicted in Table 6. As seen from the simulation results, wavelet transformation with SVM-PSO is able to detect and classify the power quality problems correctly. The classification accuracy of the SVM network is improved, just by rewriting the weights and updating of weights with cognitive as well as the social behaviour of particles along with a fitness value by PSO algorithm .The performance of SVM-PSO is compared with SVM and with other works which is shown in Table 6. From the Table 6 it is inferred that proposed method stands as an evident that it can be implemented in any online application

Table 6: Performance Comparison

Power Quality Events	Comparison of classification rate in %							
	References				Proposed			
	Martin Valtierra-Rodriguez *et al.*,2014	Prakash K. Ray *et al.*,2013	Mishra *et al.*,2008	InigoMonedero *et al.*,2007	RBFNN	SVM	SVM-PSO	SVM-PSO (30 dB Noise)
S1	100	--	100	90	100	100	100	98
S2	100	100	95	90	98	97	98	93
S3	100	97	91	70	93	98	99	94
S4	--	--	99	--	98	98	99	96
S5	--	--	96	--	96	97	99	98
S6	--	--	98	80	94	98	98	96
S7	98	--	100	--	96	96	99	94
S8	98	--	98	--	93	96	98	95

6. Conclusion

In this work, the application of wavelet transform combined with SVM technique, to detect and classify various PQ disturbances, is presented. A numerical simulation is conducted to exhibit the properties of WT-based MRA. The features extracted by wavelet are used as inputs to SVM for detection and classification. The classification accuracy of the SVM is improved by appropriate selection of features in the SVM. The performance of SVM is compared with RBFNN and with practical data from other work and also compared based on the features and number of features used with respect to time which is very much needed for on line application. The classification accuracy of the SVM network is even more improved, just by rewriting and updating the weights with the help cognitive as well as the social behaviour of particles along with fitness value. The performance of SVM-PSO is compared with other considered approach. The proposed method stands as an evident that it can be implemented in any real time applications.

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