A New Signal Processing Based Solution for PQ Disturbance Classification

Tuesday, June 11, 3:30 p.m.

TRACK B: EXPERT SYSTEMS EVENT CLASSIFICATION

Presented by Min Wang, University of Washington.

Search or print this paper using the tools menu at the top of your screen.

Return to the Agenda by clicking on the **Exit Paper and Return to PQA 2002** link or tab.

A New Signal Processing Based Solution for PQ Disturbance Classification

Min Wang, *Student Member, IEEE*, and Alexander Mamishev, *Member, IEEE*

***Abstract*--Software and hardware for automatic classification of power quality disturbances are highly needed for both utilities and commercial customers. Existing automatic recognition methods need much improvement in terms of their capability, reliability, and accuracy. This paper presents a new signal processing based approach for discriminating power quality events. A classification-driven time-frequency representation (TFR) is designed and used for feature extraction. A neural network with feed-forward structure is chosen as the classifier. The long-term applications of this technique include: enhancement of real-time power system protection, statistical analysis of power quality problems, and incipient fault detection. This algorithm is successfully demonstrated with a large number of simulated test data. An algorithm demonstration software is developed using Matlab GUI. This paper also introduces the data source for this project. The current and future research work of the SEAL lab on PQ monitoring is also discussed.**

***Index Terms*—Power Quality Disturbances, Time-Frequency Representations, Ambiguity Plane, Class-Dependent Kernel, Feature Extraction, Classifier, Feedforward Neural Networks.**

I. Introduction

Due to the increasing popularity of power electronics, power quality (PQ) related disturbances in power systems have become one of the major concerns of utility companies and commercial customers. PQ problems significantly affect many industries, particularly semiconductor industry, e-commerce, chemical industry, automobile industry, and paper manufacturing. A report by CEIDS (Consortium for Electric Infrastructure to Support a Digital Society) shows that the U.S. economy is losing between \$15 billion to \$24 billion due to PQ phenomena.

PQ monitoring has been a topic of great interest. The principal methods in utilities are primarily based on visual inspections of voltage and current waveforms. Many new methods for automatic detection and classification of PQ disturbances have been proposed recently based on wavelet analysis, artificial neural networks, hidden Markov models, and bispectra. [1-6].

However, we are not even close to a satisfactory solution to this problem yet. To build a successful PQ monitoring system, the following issues have to be addressed. First, new classification algorithms need to be verified by transients due to different power system events, such as motor starting, transformer inrush currents, capacitor switching, and high impedance faults. Transient identification problems, which require higher frequency waveform recording devices and more robust classification methods, are rarely addressed in the literature [7]. Second, new methods should be capable of implementing cause-based classifications, in addition to phenomenon-based classifications. For example, for a voltage sag event, we want to know not only that it is voltage sag, but also whether it is caused by a big load switching, or a line to ground fault, or some other reasons. Third, new methods should be able to localize a PQ event, which indirectly leads to a solution for the detected PQ problem. Multiple monitors may be needed. The number of monitors and their layout in a power system need to be optimized. Besides the three issues above, the new method should also have the computational complexity to support real-time on-line monitoring.

New methodology and techniques are currently being explored to improve the reliability and accuracy of the existing methods. This paper presents a new PQ classification algorithm, utilizing a combination of time-frequency analysis and artificial neural networks. The feature extraction scheme is based on the time-frequency ambiguity plane, and the classifier adopted is a feedforward neural network.

II. Background

A. PQ Disturbances

The fact that a PQ event varies in wide range of time and frequency makes automatic identification problems often difficult and elusive. Major power quality problems include harmonics, voltage sags, voltage swells, capacitor switching transients, big-load switching transient, and lightning strike transients.

Harmonic distortion is still the most significant power quality problem [8]. Because of the increasing popularity of electronic and other non-linear loads, such as adjustable-speed drives, arc furnaces, and induction furnaces, perfect sinusoid waveforms often become distorted in this way. Transformer core saturation is another cause of harmonic distortion. Major consequences of harmonics include equipment overheating, excessive currents and voltage, and tripping of protective relays.

Transients caused by capacitor switching are also among common sources of degradation in utility systems [8]. The

This work is supported by the Advanced Power Technologies (APT) Center at the University of Washington. The APT Center is supported by ALSTOM ESCA, CESI, LG Industrial Systems, and Mitsubishi Electric Corp.

Min Wang and Alexander Mamishev are both with the Department of Electrical Engineering, SEAL (Sensors, Energy, and Automation Laboratory), University of Washington, Seattle, WA 98195-3500, USA (e-mails: {mwang, mamishev}@ee.washington.edu).

frequency of a transient is determined mostly by the capacitance and inductance of system components. Capacitor banks are commonly used in power systems for power factor correction. Major consequences of capacitor switching events include insulation breakdown or sparkover, semiconductor device damage, short circuits, accelerated aging, and loss of data or stability.

A momentary voltage dip that lasts for a few seconds or less is classified as voltage sag. It is caused by faults, the start of large loads (e.g. motors), or brownout recovery. Major consequences of voltage sag include short circuits, process interruptions, loss of data, and accelerated aging. Process industry equipment is particularly sensitive to voltage sag problems, because the conveyor-like machinery is interconnected and a trip of any component in the process can cause the whole plant to shut down.

Voltage swells are often caused by faults, capacitor energizations, and load switchings. Major consequences of voltage swell include equipment overheating and shortened lifetime.

B. Background for the proposed algorithm

Classification of PQ events is a pattern recognition problem. The solution for a pattern recognition application usually consists of two major steps: the feature extraction and the classification. Feature extraction is to capture the key information from the objects to be classified, and supply features as inputs for the classification process. Classification is to obtain the pattern recognition results by passing the features extracted through a classifier.

Features are often extracted from some form of time-frequency representations (TFRs) in pattern recognition applications. Among the classes of correlative TFRs, ambiguity plane plays an important role. It has been used extensively in the fields of radar, sonar, radio astronomy, communications, and optics [9].

As shown in Figure 1, a signal can be mapped to an infinite number of TFRs. An optimal TFR for the classification task is necessary in the feature extraction. It has been shown that spectrogram, a popular TFR, is not an optimal TFR for any signal classification task. The objective of a spectrogram is to describe the energy density of a signal simultaneously in time and frequency domains accurately, while the goal of a classification TFR is to maximize the separability of signals from different classes. Therefore, as illustrated in Figure 1, it is desirable to design the classification-optimal TFR, a TFR_i that maximizes class distances [10]. Features are thus extracted by mapping each signal with TFR_i.

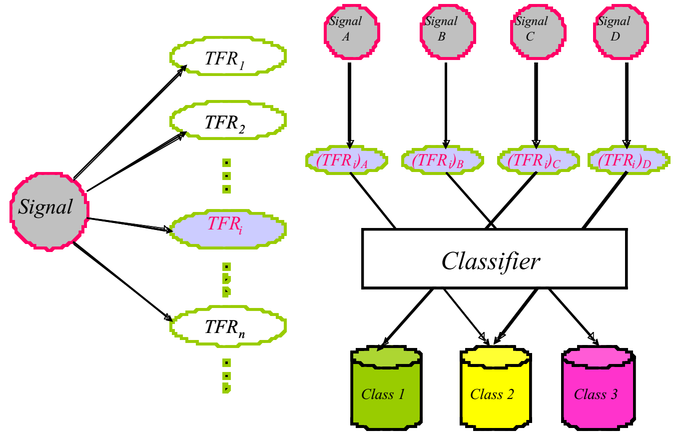


Figure 1. Feature extraction using the optimal TFR.

It is shown that any TFR can be generated from the time-frequency ambiguity plane of a given signal [11]. This means that we can derive the optimal TFR_i, by smoothing the ambiguity plane with a certain kernel function. The criterion for selecting the kernel function is to discard any redundant information and retain only the information essential for classification. This technique has been successfully applied for tool-wear monitoring and radar transmitter identification [11;12].

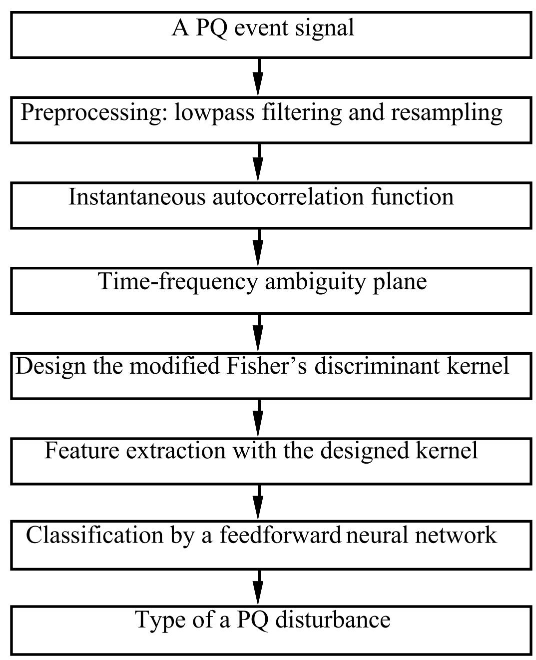


Figure 2. The proposed PQ classification algorithm.

In our algorithm for classifying power quality disturbances, the concept of ambiguity plane together with a modified Fisher's discriminate ratio kernel is used for feature extraction, essentially looking for certain form of TFR that fits the classification goal best. A neural network with feedforward structure is chosen as the classifier.

III. The Proposed PQ Classification Method

The mathematical details of the proposed classification algorithm can be found in [13]. We will only briefly introduce this algorithm in this paper. The diagram in Figure 2 shows the complete procedures of the algorithm.

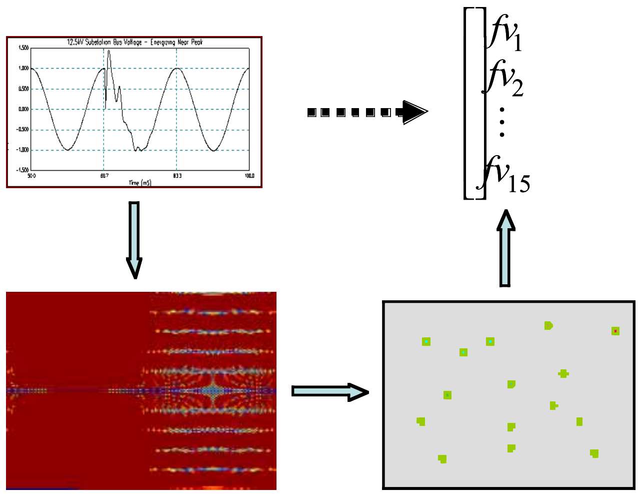


Figure 3. The feature extraction process.

The first step is to pass the original signal through a lowpass filter and downsample the signal. After this operation, the signal dimension is reduced, which results in a dramatic reduction of the computational complexity. At the same time, the high frequency electrical noise is attenuated.

The second step is to calculate the instantaneous autocorrelation function, and thus the time-frequency ambiguity plane of the input waveform [13].

The third step is to design the optimal classification-TFR by smoothing the ambiguity plane with a modified Fisher's discriminate kernel. The most important N (a number much smaller than the length of the original waveform) points on the ambiguity plane will be selected. The selection process is based on the statistics of example waveforms and involves a training process. They compose the feature vector.

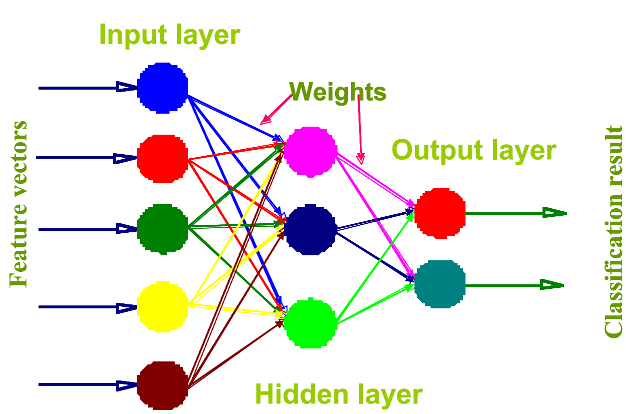


Figure 4. A feedforward neural network is used as the classifier.

Both step 2 and 3 are illustrated in Figure 3. A signal waveform is mapped to a feature vector with a much smaller dimension. This completes the feature extraction process.

The fourth step is to make the classification decisions with a neural network classifier and feature vectors. As shown in Figure 4, the neural network used has a feedforward structure. More specifically, the input layer has 15 neurons, hidden layer 10 neurons, and output layer 6 neurons.

IV. Simulations and Results

To verify the feasibility of this algorithm, a classification experiment is conducted with simulated PQ disturbances. The signals cover six major PQ classes: harmonics, capacitor fast switching transients, capacitor slow switching transients, voltage sudden sags, voltage gradual sag decays, and voltage swells.

Each example signal consists of five cycles of a voltage waveform sampled at 256 points per cycle, with up to 0.3% added randomly generated noise. We use 6000 examples (1000 per class) to design the modified Fisher's discriminate kernel and train the neural network. Another 1800 examples (300 examples per class) are used to test the classification method. The classification results are shown in Table I.

PQ Classes	M1	M2	M3	M4	M5	M6	**Correct Rate**
1. HM	-	0%	0%	0%	0%	0%	**100%**
2. CHST	0%	-	0%	0%	0%	0%	**100%**
3. CLST	0%	6%	-	0%	0%	0%	**94%**
4. VSS	0%	0%	1%	-	7%	0%	**92%**
5. VGD	0%	0%	7%	0%	-	0%	**93%**
6. VSW	0%	0%	0%	0%	0%	-	**100%**

Table I. Results of six-class PQ events classification. (Here HM indicates harmonics, CHST capacitor high frequency switching transients, VSS voltage sudden sags, and VSW voltage swells; correct rate indicates the percentage of correct identifications; Mi indicates the percentage of mistake identification to class *i*.)

V. Data Sources

Data collection is very important for this project. We acquire our experimental data through three ways.

First, we try to record all types of common PQ disturbance waveforms by handheld PQ monitoring equipment -- Dranetz-BMI Power Platform 4300, in the power distribution systems on the campus of the University of Washington.

Second, we receive PQ disturbances data from our industrial contacts.

Third, computer simulations are conducted using software packages, such as PSCAD/EMTDC and Matlab.

VI. Demonstration GUI

An algorithm demonstration GUI (Graphical User Interface) is developed with Matlab GUI. The program takes in voltage or current waveforms dynamically and outputs the classification result instantly.

As shown in Figure 5, a waveform of capacitor fast switching event is taken in, and the event type is correctly shown on the interface. This interface illustrates the whole recognition process dynamically, with a block showing the ambiguity plane of the signal piece inside the processing window, a block showing the classification-TFR (i.e., the smoothed ambiguity plane), and a block showing the neural network classifier. When the "FFT" button is pushed, the Fast Fourier Transform of the processed waveform is shown. The "View Data" and "Record" buttons can be used to view recent classification records and make PQ evaluations of the observed system. This GUI shows the potential of building a fully automated PQ monitoring system, with underground signal processing engine and user interface, for both utilities and PQ sensitive commercial customers.

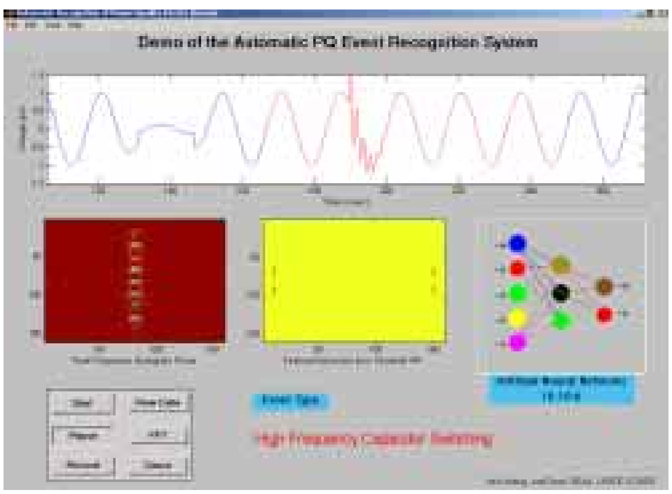


Figure 5. Demonstration GUI for the proposed algorithm.

VII. Discussions and Future Research

As mentioned in the introduction section, to build an accurate, reliable, and real-time comprehensive PQ monitoring system, problems such as the transient classification, the cause-based classification, and the event localization need to be solved. The proposed algorithm in this paper has the potentials of solving transient and cause-based classification problems, given that enough real signals are accumulated. We take a 5-cycle window size in this algorithm. This is suboptimal when the system has over-5-cycle disturbances. It can be improved by using multiple windows with different sizes. Also in the lowpass filtering and downsampling step, we use a downsampling rate of 8, which is also changeable based on the system monitored. If high frequency events happen often or are of particular interests, the downsampling needs to be done at a lower rate.

Figure 6 shows the current research work and future research directions on this topic in the SEAL (Sensors, Energy, and Automation Laboratory). Currently we are focused on PQ database accumulations and development of monitoring algorithm and software. Recent efforts have been focused on the validation of the proposed algorithm with real data. We are also exploring the cause-based classification algorithm using advanced pattern recognition techniques, such as hidden Markov models (HMM). Based on these algorithms, a web-centered real-time software with friendly user interface for utility PQ monitoring will be developed. In the near future, SEAL will move onto the hardware instrumentation of PQ monitoring equipment. One of the goals is to build handheld PQ monitors with the capability of on-line event classification and cause diagnosis. Another goal is to build a distributed PQ monitoring network. To finish these tasks, the techniques such as digital signal processors (DSPs) programming, embedded system design and development, and communications will be involved.

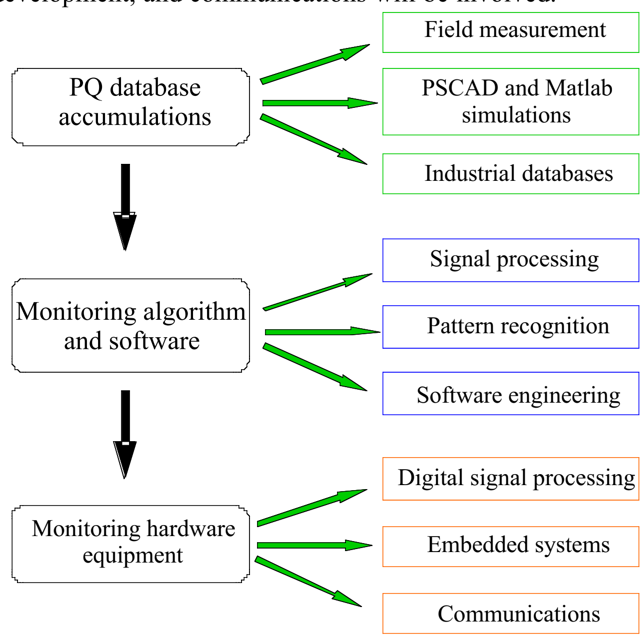


Figure 6. Current and future PQ research directions in SEAL.

VIII. Conclusions

A new classification method for PQ is proposed and demonstrated successfully with simulated PQ events in this paper. This algorithm is based on the time-frequency ambiguity plane, the modified Fisher's discriminate kernel, and the artificial neural network. The mathematical details of this algorithm can be found in our recent paper[13]. An algorithm demonstration GUI is also presented in this paper.

The paper also discusses several issues to be addressed in PQ waveform identifications. The authors indicate that more research is needed before a satisfactory solution can be achieved for accurate and reliable PQ monitoring.

IX. Acknowledgments

This work is supported by the Advanced Power Technologies (APT) Center at the University of Washington. The APT Center is supported by ALSTOM ESCA, CESI, LG Industrial Systems, and Mitsubishi Electric Corp.

We gratefully acknowledge the contributions of UW EE graduate and undergraduate students Piotr Ochenkowski, Rejo Jose, Jeffrey Chen, Rhea Frondozo, and Thuy Hoang, for their work on the data collection and simulations of this project. We also wish to thank James Harris from BPA (Bonneville Power Administration), Joe Wilson from EWEB (Eugene Water & Electric Board), Yakov Shlemenzon from R.W. Beck, Steve Sturgill from SRP (Salt River Project), and Mark Kirschenbaum from the University of Washington Physical Plant, for their help on the real data.

X. References

[1] S. Santoso, E. J. Powers, W. M. Grady, and A. C. Parsons, "Power quality disturbance waveform recognition using wavelet-based neural classifier. I. Theoretical foundation," *IEEE Transactions on Power Delivery*, vol. 15, no. 1, pp. 222-228, Jan.2000.

[2] A. M. Gaouda, M. A. Salama, M. R. Sultan, and A. Y. Chikhani, "Power quality detection and classification using wavelet-multiresolution signal Decemberomposition," *IEEE Transactions on Power Delivery*, vol. 14, no. 4, pp. 1469-1476, Oct.1999.

[3] J. Chung, E. J. Powers, W. M. Grady, and S. C. Bhatt. Electric Power Transient Disturbance Classification Using Wavelet-based Hidden Markov models. 3662-3665. 2000. Proceedings of 2000 IEEE International conference on Acoustics, Speech, and Signal Processing. ICASSP'00.

[4] B. Perunicic, M. Mallini, Z. Wang, and Y. Liu. Power quality disturbance detection and classification using wavelets and artifial neural networks. 1, 77-82. 1998. 8th International conference on Harmonics and Quality of Power Proceedings.

[5] X. Chen. Wavelet-based detection, localization, quantification and classification of short duration power quality disturbances. 2, 931-936. 2002. IEEE Power Engineering Society Winter Meeting, 2002.

[6] J. S. Lee, C. H. Lee, J. O. Kim, and S. W. Nam. Classification of power quality disturbances using orthogonal polynomial approximation and bispectra. Electronics Letters 33[18], 1522-1524. 1997.

[7] A. V. Mamishev, S. X. Short, T. W. Kao, and B. D. Russell, "Analysis of High Impedance Faults Using Fractal Techniques," *IEEE Transactions on Power Systems*, vol. 11, no. 1, pp. 435-440, 1996.

[8] R. C. Dugan, M. F. McGranaghan, and H. W. Beaty, *Electrical Power Systems Quality* McGraw-Hill, 1996.

[9] F. Hlawatsch and G. F. Boudreaux-Bartels, "Linear and quadratic time-frequency signal representations," *IEEE Signal Processing Magazine.*, vol. 9, no. 2, pp. 21-67, Apr.1992.

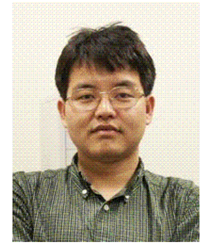
[10] J. McLAugusthlin, J. Droppo, and L. Atlas. Class-dependent, discrete time-frequency distributions via operator theory. 3, 2045-2048. 1997. IEEE International conference on Acoustics, Speech, and Signal Processing (ICASSP).

[11] B. W. Gillespie and L. Atlas. Data-driven time-frequency classification Techniques applied to tool-wear monitoring. 2, 2045-2048. 2000. Proceedings of the 2000 IEEE ICASSP.

[12] B. W. Gillespie and L. Atlas. Optimization of time and frequency resolution for radar transmitter identification. 3, 1341-1344. 1999. Proceedings of the 1999 IEEE ICASSP.

[13] M. Wang, P. Ochenkowski, and A. V. Mamishev. Classification of power quality disturbances using time-frequency ambiguity plane and neural networks. 2, 1246-1251. 2001. IEEE Power Engineering Society Summer Meeting, 2001.

XI. Biographies



Min Wang received a B.S. degree from Tsinghua University, Beijing, China, in 1999, and a M.S. degree in electrical engineering from the University of Washington, Seattle, in 2001. Currently he is a Ph.D. student and research assistant at the Department of Electrical Engineering, University of Washington. His research and study interests include signal processing, power quality monitoring, and software engineering. He is a student member of IEEE PES.

Alexander Mamishev received an equivalent of B.S. degree from the Kiev Polytechnic Institute, Ukraine, in 1992, M.S. degree from Texas A&M University in 1994, and a Ph.D. degree from MIT in 1999, all in electrical engineering. Currently he is an assistant professor and director of SEAL (Sensors, Energy, and Automation Laboratory) in the Department of Electrical Engineering, University of Washington, Seattle. Prof. Mamishev is an author of about 40 journal and conference papers, and one book chapter. His research interests include PQ monitoring, sensor design and integration, dielectrometry, and electrical insulation diagnostics. He serves as a reviewer for IEEE Transactions on Power Delivery and IEEE Transactions on Dielectrics and Electrical Insulation. He is a recent recipient of NSF CAREER Award and IEEE Outstanding Branch Advisor Award.