

Power Quality Events Classification Using ANN

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ABSTRACT

Classification of power quality events (PQE) related voltage and current waveform fluctuations is a key task for evaluating power system performance. Power quality disturbances such as voltage sags, swells, interruptions, harmonics, and capacitor switching events adversely affect sensitive loads and system reliability. In this paper, a power quality event classification method based on optimized time-frequency representation (OTFR) and artificial neural networks (ANN) is presented. The proposed approach involves two main stages: feature extraction and classification. The optimized time-frequency representation is designed to highlight distinguishing characteristics of PQE waveforms in a low-dimensional space, enabling effective separation among different disturbance classes. A set of kernels is designed for different PQE categories, and Fisher's discriminant score is used to select optimal feature locations on the time-frequency ambiguity plane. The extracted features are then applied to linear classifiers and feed-forward neural network classifiers for final classification. The proposed classification algorithm has been tested and verified using real-world power quality data comprising five classes. Furthermore, the algorithm is implemented on a DSP-based real-time hardware system to validate its computational efficiency. Experimental results demonstrate high classification accuracy and fast processing capability, confirming the suitability of the proposed method for real-time power quality monitoring applications.

Keywords: Power Quality Events, Optimal Time-Frequency Representation, Artificial Neural Network, DSP Implementation, Classification

1. INTRODUCTION

The PQE classification approach consists of two sequential processes: feature extraction and classification. Feature extraction aims to project PQE waveforms onto a low-dimensional time-frequency representation (TFR) to enhance discrimination among different disturbance classes. Distinct TFRs are designed to separate one class or a group of classes from others. Linear classifiers and artificial neural networks with feed-forward structures are used for classification. The algorithm has been tested with five PQE classes including voltage sags, swells, capacitor switching events, interruptions, and normal voltage variations.

2. OPTIMAL TFR DESIGN AND CLASSIFIER TRAINING

A dataset of 250 real-world voltage waveforms consisting of 50 signals from each PQE class is used for kernel design and classifier training. Since five classes are considered, four kernels are required. Table 1 . Harmonics Kernel

Location Co-ordinates	score J F1	Whether selected for feature location?
(22, 32)	33.94	Yes
(22, 612)	33.94	No, symmetric with (22, 31)
(622, 612)	33.94	No, symmetric with (22, 32)
(622, 32)	33.9499	No, symmetric with (22, 31)
All other locations	< 33.94	No

Table 2: Voltage Sag Kernel

Location values	Discriminant score, JF2	Whether selected for feature location?
(257, 3)	5.06	Yes
(257, 640)	5.06	No, symmetric with (257,3)
(385, 3)	5.0649	No, symmetric with (257, 3)
(385, 640)	5.06	No, symmetric with (257, 2)
(258, 3)	4.99	Yes
(258, 640)	4.99	No, symmetric with (258, 3)
(384, 2)	4.99	No, symmetric with (258, 3)
(384, 640)	4.9953	No, symmetric with (258, 3)

All other	< 4.9953	No
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These include harmonics, voltage sag, capacitor switching, and capacitor high-frequency switching kernels. Fisher's discriminant score is used to rank feature locations on the ambiguity plane, and optimal feature points are selected based on classification performance..

Table 1 and Table 2 show the process for designing only two kernels. Likewise rest two kernels can be designed. The number of feature points needed for every kernel is found by rigorous classification experiments[9-10]. The number of feature points is found from min to max, starting from 1. The optimal numbers of feature points for every kernel have been searched. Hence, nine feature locations are chosen for these four kernels. In Table 1 and Table 4, the column "Location" means the coordinate (n, t) on time-frequency ambiguity plane, where n represents discrete frequency shift(DFS), and t represents discrete timelag(DT) [1]. To design the kernel i , total 640×640 locations on the ambiguity plane are ranked based on their Fisher's discriminant (FD)scores J_{Fi} ($i=1,2,3,4$)[2], whose computation method is governed by equation (8) in [1]. The correlations of locations on the ambiguity plane are taken in the feature selection process. Because moduli of the points on the ambiguity plane are symmetric in nature according to both horizontal and vertical axes of the plane, always a group of four locations has identical Fisher's discriminant score(FDS). One of these four locations is selected as a feature location..

3. WAVEFORM PROCESSING ALGORITHM

For a 640-point input waveform, nine feature points are extracted using the designed kernels. These feature values are serially fed into linear and ANN classifiers to determine the corresponding PQE class. The processing flow ensures accurate classification with minimal computational delay.

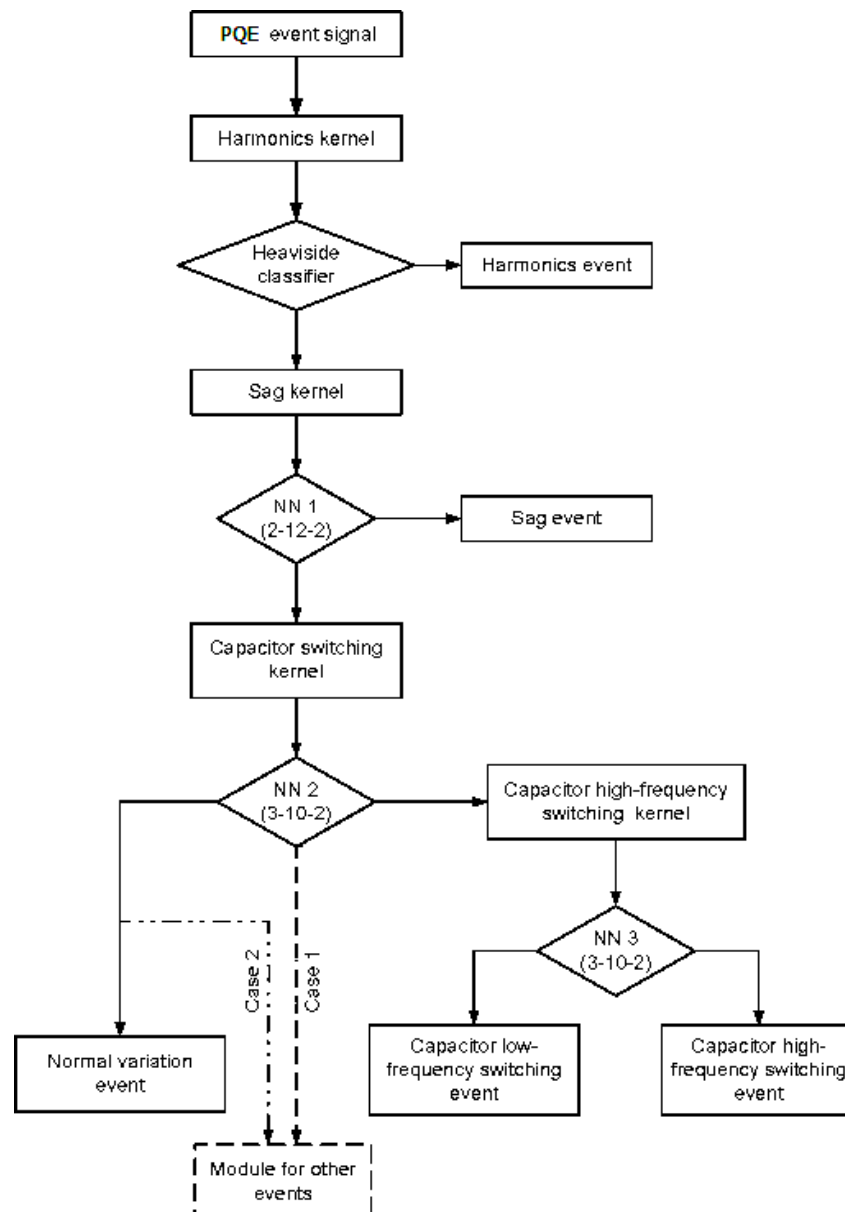


Fig. 3.1 PQE signal classification algorithm

4. DSP-BASED REAL-TIME HARDWARE IMPLEMENTATION

The algorithm is implemented on a DSP-based hardware platform using the TI TMS320VC5XXX processor and a 12-bit 6-MSPS ADC. The system supports real-time monitoring and testing modes. Performance evaluation confirms that a five-cycle PQE waveform can be processed within 11.2 ms, validating real-time capability. To evaluate and verify the real-time computing capability of algorithm, a DSP-based hardware system is implemented with proposed algorithm.

A block diagram for the system is shown in Fig.4.1 The algorithm is implemented with TI TMS320VC5XXX digital signal processor with TI THS1206 12-bit 6 MSPS A/D converter. In deployment mode, signal is passed through a potential transformer and then through ADC. In the testing mode, signal is fed either from a function generator or from a PC station .While response time of the system is observed and measured.

The TMS302VC5XXX is a fixed-point DSP processor having 128 KB of on-chip memory with 160 MHz clock speed, which can perform 160 MIPS. This DSP processor has a 17x17 parallel multiply accumulator unit which permits single cycle multiply accumulate operations.

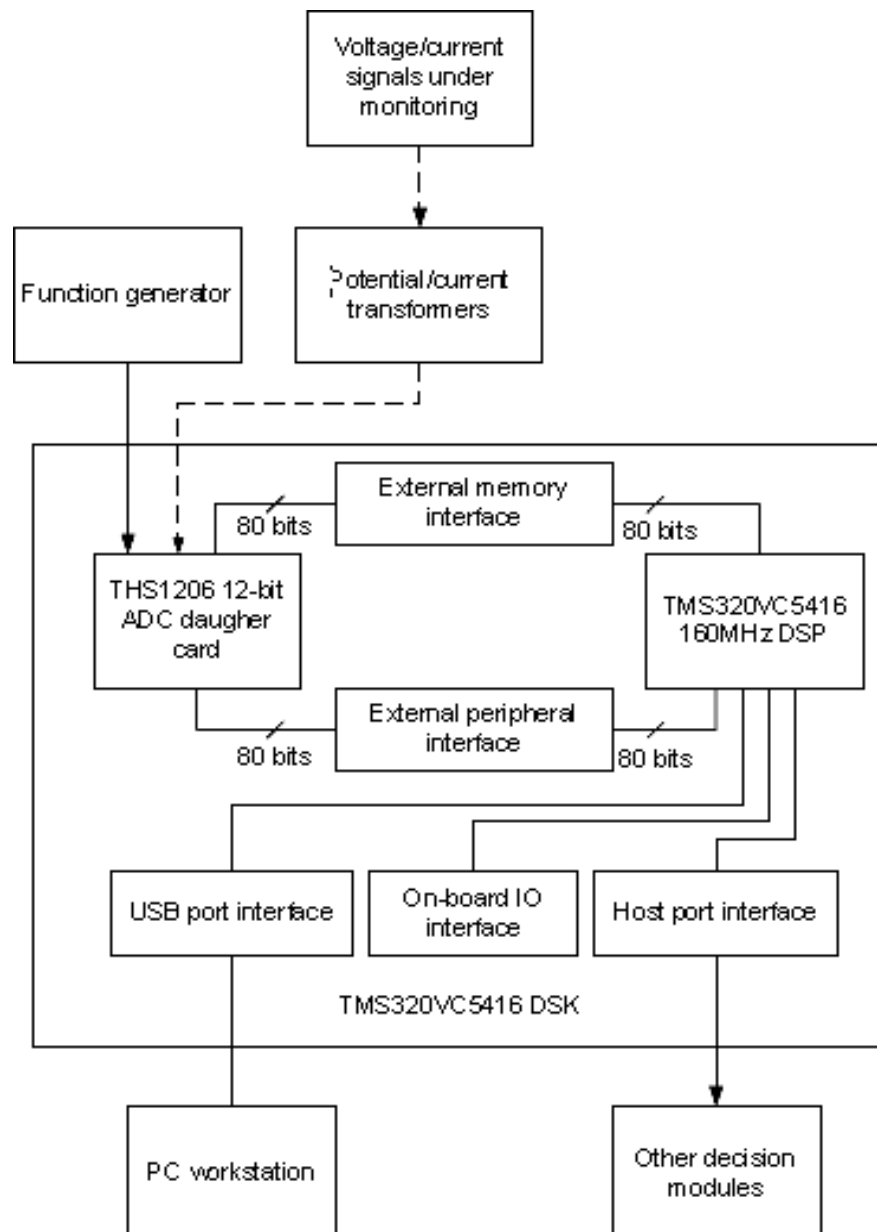


Fig.4.1-Block diagram of the hardware PQE monitoring system

5. EXPERIMENTAL RESULTS

Experimental results demonstrate high recognition accuracy across all PQE classes. The overall classification accuracy achieved is approximately 99%, confirming the robustness and reliability of the proposed method. The detailed results are shown in table 5.1 and table 5.2 for various discussed PQE classifications.

TABLE 5.1. STEP-BY-STEP RESULTS

Kernels acting	Signals in class			Signals in rest of classes		
	Testing events	Recognized events	Recognition rate	Testing events	Recognized events	Recognition rate
1. Harmonics	203	199	99%	657	656	99%
2. Sags	145	144	99%	516	515	99 %
3. Capacitor switching	176	172	98.0%	317	311	98%
4. Capacitor high-frequency switching	138	135	98%	179	172	96%

TABLE 5.2 RESULTS OF A POWER QUALITY EVENTS CLASSIFICATION EXPERIMENT WITH DIFFERENT PQE DATA

Different Classes	Testing events	Recognized events	Recognition rate
1. Harmonics	203	199	99%
2. Voltage sags	145	144	99%
3. Capacitor low-frequency switching	176	172	98%
4. Capacitor high-frequency switching	138	135	98%
5. Normal voltage variations	198	194	98.0%
Total	860	844	99.0%

6. CONCLUSIONS

An effective PQE classification method based on optimized time-frequency representation and artificial neural networks has been presented. The proposed system achieves high classification accuracy and real-time performance. Future work includes extending the approach to handle simultaneous PQ disturbances.

7. REFERENCES

- [1] [1] M. Wang and A. V. Mamishev, "Classification of Power Quality Events Using Optimal Time-Frequency Representations -- Part 1: Theory," IEEE Transactions on Power Delivery, 2003.
- [2] S. Santoso, E. J. Powers, W. M. Grady, and A. C. Parsons, "Power Quality Disturbance Waveform Recognition Using Wavelet-Based Neural Classifier. II. Application," IEEE Transactions on Power Delivery, vol. 15, no. 1, pp. 229- 235, Jan. 2000.
- [3] J. Chung, E. J. Powers, W. M. Grady, and S. C. Bhatt, "Electric Power Transient Disturbance Classification Using Wavelet-Based Hidden Markov Models," Proceedings of 2000 IEEE International Conference on Acoustics, Speech, and Signal Processing, vol. 6, 2000, pp. 3662-3665.
- [4] K. Fodero, C. Huntley, and D. Whitehead, "Wide-Area Time Synchronization for Protection," proceedings of the 36th Annual Western Protective Relay Conference, Spokane, WA, October 2009.
- [5] J. Roberts, D. Tziouvaras, G. Benmouyal, and H. Altuve, "The Effect of Multiprinciple Line Protection on Dependability and Security," proceedings of the 55th Annual Georgia Tech Protective Relaying Conference, Atlanta, GA, May 2001.
- [6] A. Guzmán, C. Labuschagne, and B.-L. Qin, "Reliable Busbar and Breaker Failure Protection With Advanced Zone Selection," proceedings of the 31st Annual Western Protective Relay Conference, Spokane, WA, October 2004.
- [7] A. Guzmán, N. Fischer, and C. Labuschagne, "Improvements in Transformer Protection and Control," proceedings of the 62nd Annual Conference for Protective Relay Engineers, College Station, TX, March 2009.
- [8] M. Wang, P. Ochenkowski, and A. V. Mamishev, "Classification of Power Quality Disturbances Using Time- Frequency Ambiguity Plane and Neural Networks," IEEE Power Engineering Society Summer Meeting, 2001, vol. 2, 2001, pp. 1246-1251.
- [9] B. W. Gillespie and L. Atlas, "Optimizing Time-Frequency Kernels for Classification," IEEE Transactions on Signal Processing, vol. 49, no. 3, pp. 485-496, Mar. 2001.