Power Disturbance Recognition Using Probabilistic Neural Networks

Chau-Shing Wang, Wen-Ren Yang, Jing-Hong Chen, and Guan-Yu Liao

Abstract—**This paper presents power disturbance recognition using discrete wavelet transform (DWT) and probabilistic neural networks (PNN). The DWT is first used to extract the features of the power disturbances. The Parseval theory is utilized to calculate the energy of each level so that the number of coefficients can be reduced; then, the extracted results are used for recognition by the PNN. Further, the Matlab and LabVIEW are used to generate the power disturbance waveforms for testing. From testing results, the recognition rate is at least 86 %. It proves the feasibility of the proposed method.**

Index Terms—**Discrete wavelet transforms (DWT), probabilistic neural networks (PNN), Parseval theory.**

I. Introduction

Because of rapid developments of technology and increasing usage of precision instruments in recent years, higher power quality is required to avoid the malfunction of equipment. To reduce the losses caused by the poor power quality, we need some electronic detection, classification, and recording devices to monitor the system behavior, so that we can find out the causes and the kinds of power quality events and then try to improve the quality.

According to the periodicity of power disturbances, they can be classified as stationary or non-stationary signals [1-2]. For many stationary signals, Fourier analysis is a useful analysis tool because the frequency content is of great importance in formation. Practical measurements using Fourier Transform (FT) assume infinite periodicity of the signal to be transformed. Furthermore, the time-domain information in the signal would be spread out on the whole frequency axis and become unobservable following the transformation. Therefore, this method is not suitable for analyzing non-stationary signals.

To correct this deficiency of FT, the Short-Time Fourier Transform (STFT) is proposed, which maps a signal into a two-dimensional function of time and frequency. The STFT extracts time-frequency information. However, the disadvantage is that the size for the time-window is fixed for all frequencies. The wavelet analysis represents a windowing technique with variable-sized regions to improve the deficiency [3-4].

Manuscript received December 28, 2008. This work was supported by the National Science Council in Taiwan (NSC96-2628-E-018-014-MY2).
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Therefore, this paper uses wavelet based probabilistic neural networks (WPNN) to recognize the power quality event, which is proved being capable of classifying the event with multiple power quality disturbances.

II. Wavelet Analysis

Recently, wavelets theory has been applied in variety of research areas such as signal analysis, data processing and compression. The main feature of wavelets is the oscillating and has average value of zero as well as the major advantage afforded by wavelets is the ability to perform local. Wavelet analysis is capable of revealing aspects of data that other signal analysis techniques miss, aspects such as trends, breakdown points etc.

Generally, smooth wavelets indicate higher frequency resolution than wavelets with sharp steps; the opposite applies to time resolution. One of the most widely used mother wavelets suitable for power quality analysis is the Daubechies (db) wavelet. The mother wavelets function is define as:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \qquad (1)$$

$$where \quad \begin{cases} a: scale \quad parameter \\ b: shift \quad parameter \end{cases}$$

This wavelet analysis is particularly suitable for detecting low amplitude, short duration, fast decaying and oscillating type of signals, encountered frequently in power systems, which is a popular signal analysis method, offers continuous and discrete wavelet transforms (CWT and DWT). The DWT is defined as:

$$DWT_x^{\psi}(a,b) = \frac{1}{\sqrt{a}}\int x(t)\psi^*(t) \qquad (2)$$

$$where \quad \left.\begin{matrix} a = 2^m \\ b = na \end{matrix}\right\} \quad m,n \in Z$$

$$\psi(t) \quad is \quad given \quad in \quad (1)$$

The DWT can realize a time domain signal into time-frequency domain using a multi-stage filter to implement, low frequency filter $g(t)$ and high frequency filter $h(t)$, and the low pass filter $g(t)$ and the high pass filter $h(t)$ can be calculated using Matlab, defined as:

$$h(K-1+k) = (-1)^k g(k) \qquad (3)$$

With the mother wavelet function $\psi(t)$ as the low pass filter and the scaling function $\phi(t)$ as the high pass filter. The mother wavelet and scaling function are defined as:

$$\begin{aligned} \psi(t) &= \sum_k h(k)\phi(2t-k) \\ \phi(t) &= \sum_k g(k)\phi(2t-k) \end{aligned} \qquad (4)$$

The multi-stage filter technique, called Multi-resolution analysis (MRA)[5-6], is described by Fig.1:

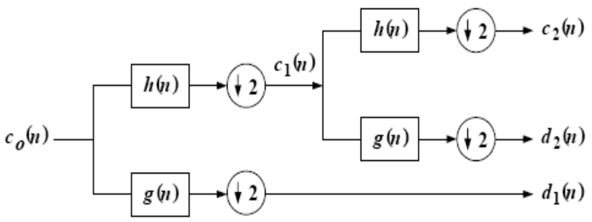

Fig. 1. Multiresolution signal decomposition (MSD) diagram.

From the Multi-Resolution Analysis (MRA), we can obtain decomposed signal at scale one, where the approximate parameter $c_1(n)$ is the smooth version of the original signal and detail parameter $d_1(n)$ is the detailed version. They are defined as:

$$\begin{aligned} c_1(n) &= \sum_k h(k-2n)c_0(k) \\ d_1(n) &= \sum_k g(k-2n)c_0(k) \end{aligned} \qquad (5)$$

And then the high pass filter is based on approximate parameter $c_1(n)$, the decomposed $c_2(n)$ and $d_2(n)$ at scale two are given as:

$$\begin{aligned} c_2(n) &= \sum_k h(k-2n)c_1(k) \\ d_2(n) &= \sum_k g(k-2n)c_1(k) \end{aligned} \qquad (6)$$

Therefore, the output of the high pass filter gives the detailed version of the high-frequency component of the signal. In contrast, the low pass filter provides the approximate version of the low-frequency component, which is then further split to go through other high pass and low pass filters to obtain the next level of the detail and approximation versions. By conducting this process, the DWT can be implemented to extract the feature of detected signal.

The DWT results are initially a series of coefficients in each level. The Parseval theory, defined in (7), is utilized to calculate the energy of each level so that the number of coefficients can be reduced. Then, the Probabilistic Neural Network (PNN) is adopted to recognize the power disturbances.

$$\int |f|^2 dt = \sum_{k=-\infty}^{+\infty} |c(t)|^2 + \sum_{j=0}^{+\infty} \sum_{k=-\infty}^{+\infty} |d_j(t)|^2 \qquad (7)$$

III. Probabilistic Neural Network (PNN)

Artificial neural network is made of many neurons connected with each other. In this paper, the proposed recognition is carried out in sets of multiple neural network using a Probabilistic Neural Network (PNN).The Probabilistic Neural Network (PNN) was presented by D. F. Specht in 1988, [7], it is forward feed networks built with three layers as shown in Fig. 2., which was developed to construct the probability density functions (PDF) required by Bayes' theory, and the network architecture's learning speed is very fast and it is indispensable to have tolerance of making information mistake, so making it suitable for signal recognize and classification in real-time. The PNN trains immediately but execution time is slow and it requires a large amount of space in memory. It only works for classifying data. The training set must be a thorough representation of the data. Probabilistic neural networks handle data that has spikes and points outside the norm better than other neural nets. Fig.3 shows the PNN architecture that is composed of competitive layer and radial basis layer.

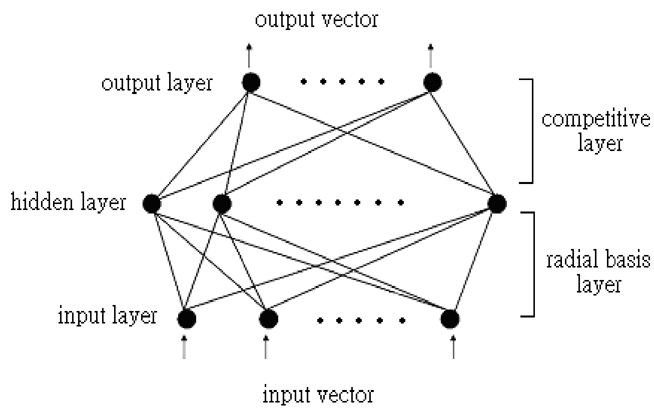

Fig.2 Architecture of a three-layers PNN

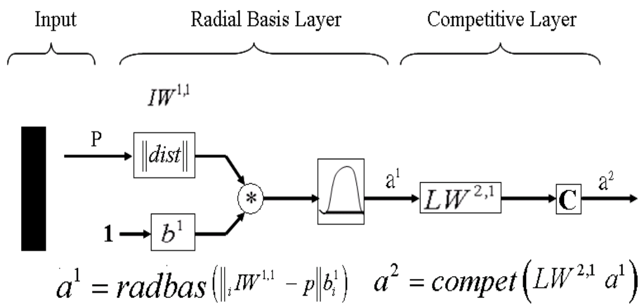

Fig.3 The detail of a PNN

The PNN has three assumptions as follow:

(1) The type attitude of probability density functions (PDF) of classifications is the same.

(2) The type attitude of probability density functions (PDF) is the Gaussian distribution:

$$f_k(x) = \left(\frac{1}{N_k}\right)\sum_{i=1}^{N_k} f_{ki}(x) \qquad (8)$$

$$f_{ki}(x) = \left(\frac{1}{(2\pi)^{m/2}}\right)\left(\frac{1}{|\Sigma|^{1/2}}\right)\exp\left(-\frac{1}{2}A'[\Sigma]^{-1}A\right) \qquad (9)$$

$$A = X - X_{ki} \qquad (10)$$

(3) The Covariance Matrix of Gaussian distribution probability density functions (PDF) of classifications is diagonal matrix, and the values of every diagonal elements are the same. Thus the above equation can be simplified as:

$$f_{ki}(x) = \left(\frac{1}{(2\pi)^{m/2}}\right)\left(\frac{1}{\sigma^m}\right)\exp\left(-\frac{\|A\|}{2\sigma^2}\right) \qquad (11)$$

where

X	:	Input vector.
$f_k(x)$	:	The PDF of k_{th} classification belonged to input vector.
$f_{ki}(x)$	:	The j_{th} PDF of k_{th} classification belonged to input vector.
π	:	Ratio of circumference.
$\|\Sigma\|$	:	The value of determinant of covariance matrix.
$[\Sigma]$	:	Covariance matrix.
X_{ki}	:	Input vector of training examples.
N_k	:	Number of k classifications.
A	:	The difference between X and X_{ki} vector.
A'	:	The transpose of the difference between X and X_{ki} vector.
$\|A\|$	:	The Euclidean distance between X and X_{ki} vector.
σ	:	Smoothing parameter.

IV. Power Disturbance Simulator and Test

The power disturbance recognizer, wavelet-based Probabilistic Neural Network, presented in this work is designed to recognize seven types of power quality disturbances, such as flicker, harmonics, interrupt, pure sine wave, dip, surge, and swell. The seven types of power disturbance are produced by LabVIEW, a very useful A/D-D/A card's software tool for signal process. It can collect or output signal by A/D card, and has many digital processing and the operation tool. It is very easy to calculate the waveform value and demonstrate the output waveform signal immediately on the screen [8-9]. Fig.4 is the waveform production system construction and Fig.5 is its software structure. Therefore, in the signal analysis, it is very convenient auxiliary software.

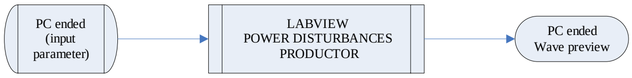

Fig.4 Construction of waveform production system

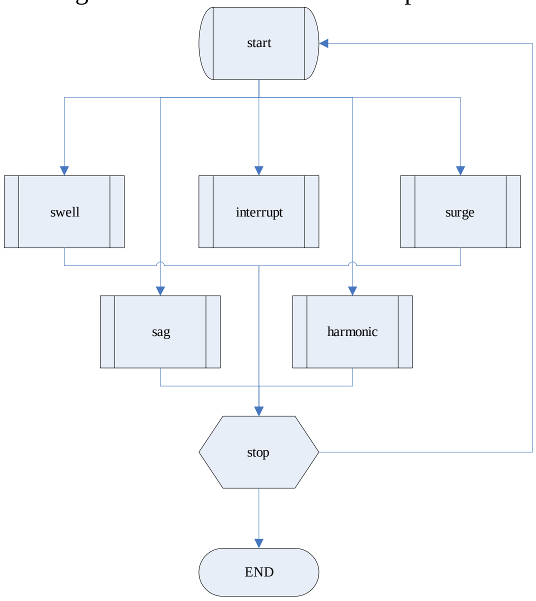

Fig.5 Software structure

A. Harmonic distortion simulation

We need to decide the condition of the harmonic distortions. The user must establish the order of harmonic, the amplitude and the phase angle of the Harmonic distortion waveform. The Harmonic amplitude and the phase angle are expressed by the matrices separately. Fig.6 is harmonic distortion waveform control window.

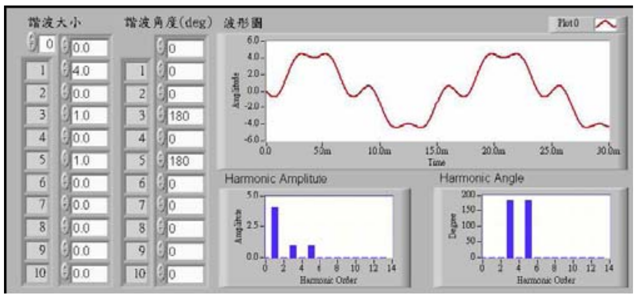

Fig.6 Harmonic waveform simulation

B. Voltage flicker simulation

In the program, the formula to calculate the voltage flicker is

$$V = \sqrt{2}V_{rms}\left[1+\frac{1}{2}\sum \Delta V_n \sin(2\pi f_n t + \theta_n)\right]\cdot \sin(2\pi \cdot 60 \cdot t) \qquad (12)$$

We must select the V_{rms}, V_n, f_n, and θ_n to setup the voltage flicker waveform. Fig.7 is voltage flicker waveform control window.

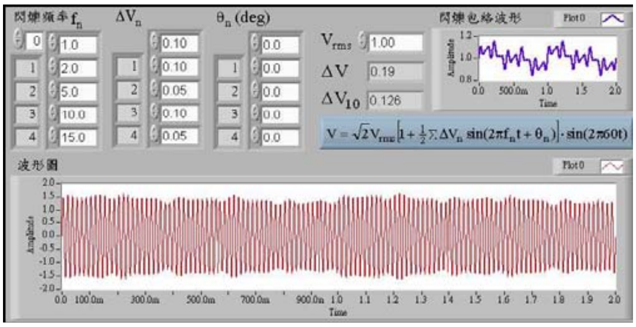

Fig.7 Flicker waveform simulation

C. Sag 、swell and interruption simulation

We need to decide parameters of these three waveform events. Fig.8 is the sag voltage waveform control window, and the small waveform window is the sag envelope curve. If we need a swell waveform, we only change the depth parameter to a negative number. If we need an interruption waveform, we only change the depth parameter to 100%.

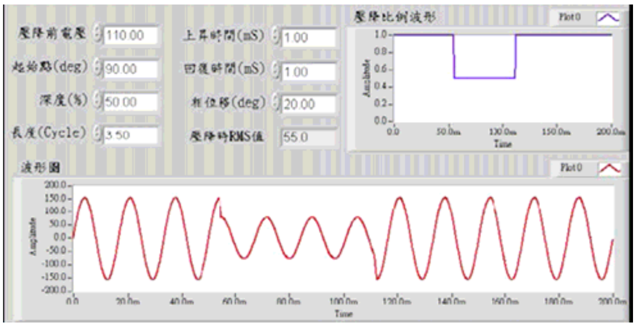

Fig. 8 Sag waveform simulation

D. surge voltage simulation

In the program, the formula to calculate the surge voltage is

$$V = V_s \cdot \sin(2\pi \cdot f_s \cdot t + \theta_s) e^{-D_s t} \tag{13}$$

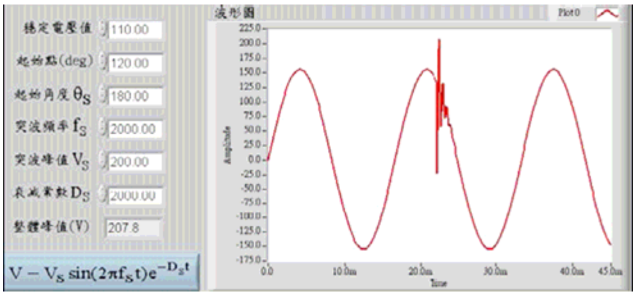

Fig. 9 Surge waveform simulation

V. Experimental Results

The structure of PNN includes input layer with 16 neurons, one hidden layer with 16 neurons and output layer with 12 neurons. Hidden layer contains Gauss transfer functions; output layer contains constant functions. Figure 10 shows the convergence of the PNN training stage. Each event has 60 waveforms for training and 40 for testing. The recognition result is shown in table1. The experimental result tells that the PNN combined with the discrete wavelet transforms has ability to recognize power disturbances accurately.

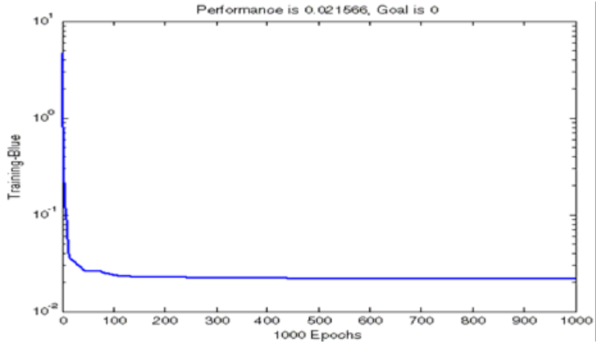

Fig.10 The converging error of PNN training

Table 1. Recognition rate of power disturbances using the DWT and PNN

Disturbance types	Recognition rate (%)
Flicker	93.1
Harmonics	91.6
Interrupt	86.5
Pure sine wave	91.5
Dip	92.6
Surge	91.6
Swell	91.7

VI. Conclusion

The purpose of this paper is to use wavelet based probabilistic neural networks to recognize power disturbance events. To test the recognition rate of the proposed method, we successfully use Matlab and LabVIEW to generate the power disturbance waveforms. From the PNN testing results, the recognition rate is at least 86 %. It proves the feasibility of the proposed method.

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