Energy and Power Engineering, 2013, 5, 561-565
doi:10.4236/epe.2013.54B107 Published Online July 2013 (http://www.scirp.org/journal/epe)

Power Quality Disturbance Classification Method Based on Wavelet Transform and SVM Multi-class Algorithms

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Received March, 2013

ABSTRACT

The accurate identification and classification of various power quality disturbances are keys to ensuring high-quality electrical energy. In this study, the statistical characteristics of the disturbance signal of wavelet transform coefficients and wavelet transform energy distribution constitute feature vectors. These vectors are then trained and tested using SVM multi-class algorithms. Experimental results demonstrate that the SVM multi-class algorithms, which use the Gaussian radial basis function, exponential radial basis function, and hyperbolic tangent function as basis functions, are suitable methods for power quality disturbance classification.

Keywords: Power Quality; Disturbance Classification; Wavelet Transform; SVM Multi-Class Algorithms

1. Introduction

Increasingly superior electrical power supply has become necessary with the development and extensive application of electricity and electronics technology. However, all types of non-linear impact loads worsen electrical energy pollution. Given this backdrop, researchers have directed considerable attention to power quality disturbance classification because of its ability to determine the cause of energy disturbance and improve power quality. This approach is currently an important area of research on power systems.

The commonly used methods for extracting power disturbance features are wavelet transforms [1], Fourier transforms [2], and S transforms [3]. These techniques share certain attributes and can effectively extract energy characteristics. Nevertheless, the accuracy of these classification methods is tremendously affected by environmental noise. Other available methods include neural network classification [4], support vector machine [5], and particle swarm optimization [6], which is typically used to classify disturbance signals. These methods are similar in that they require effective training samples, as well as present high classification accuracy, high computational complexity, and weak classification for multi-class samples.

In this paper, we use the wavelet analysis method to extract the effective feature vectors of power quality disturbances, and regard these vectors as SVM training samples. We take advantage of multi-class SVM in classifying different power disturbance scenarios, such as voltage sag, voltage swell, voltage interruption, pulse transient, and harmonic classification. Multi-class SVM presents higher classification accuracy and efficiency in power systems than do other classifiers.

2. Feature Vectors of Extraction Based on Wavelet Transform

The wavelet transform concept was originally proposed by French geophysicist J. Morlet in 1984. Theoretical physicist A. Grossman established the theoretical system of wavelet transform on the basis of the theory of translation and scale invariance. French mathematician Y. Meyer constructed the first wavelet.

The Fourier transform is a useful tool for analyzing the frequency components of a signal. However, the window length used in this operation limits frequency resolutions. Wavelet transforms are based on small wavelets with limited durations; thus, they present higher frequency resolutions at low frequencies and low time resolutions. They also exhibit higher time resolutions and lower frequency resolutions at high frequencies. With these properties, wavelet transforms are adaptive to signal analysis.

Wavelet transform involves the displacement of basic wavelet functions $\psi(t)$. Then, the inner products of signals $x(t)$ and $\psi(t)$ are calculated under different scales thus:

$$WT_x(a,\tau)=\frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty}x(t)\psi^*\left(\frac{t-\tau}{a}\right) \quad a>0; \qquad (1)$$

where τ is the translating parameter that indicates the region of interest; a denotes the scaling parameter or scale, and measures the degree of compression. In the frequency domain, this function is expressed as

$$WT_x(a,\tau)=\frac{\sqrt{a}}{2\pi}\int_{-\infty}^{+\infty}x(\omega)\psi^*\left(a\omega\right)e^{j\omega\tau}d\omega, \qquad (2)$$

where $x(\omega)$ is the Fourier transform of $x(t)$; $\psi(\omega)$ is the Fourier transform of $\psi(t)$.

Selecting an appropriate wavelet converts $\psi(t)$ in the time domain into a finite support and turns $\psi(\omega)$ in the frequency domain into a relatively concentrated variable. Implementing wavelet transform in the time and frequency domains also characterizes local signal features. The energy distribution of various power disturbance signals differs at various frequency bands. Thus, we can incorporate different energy distributions in different frequency bands as bases for distinguishing power disturbances.

On the basis of references [7, 8], we choose sym4 as the mother wavelet, and decompose power disturbance signals into 11 layers. A total of 23 characteristic values constitute a feature vector. $V_1 \sim V_{11}$ represents the quadratic sum of the eleventh to the first layers of coefficients. $V_{12} \sim V_{23}$ are calculated as follows [9]:

$$V_{12}=\frac{std\left|D_{11}\right|}{mean\left|D_{11}\right|},\ V_{13}=\frac{std\left|D_{10}\right|}{mean\left|D_{10}\right|},$$

$$V_{14}=\frac{std\left|D_{11}\right|}{mean\left|D_{11}\right|},\ V_{15}=\frac{std\left|D_{8}\right|}{mean\left|D_{8}\right|},$$

$$V_{16}=\frac{std\left|D_{7}\right|}{mean\left|D_{7}\right|},\ V_{17}=\frac{std\left|D_{6}\right|}{mean\left|D_{6}\right|},$$

$$V_{18}=\frac{std\left|D_{5}\right|}{mean\left|D_{5}\right|},\ V_{19}=\frac{std\left|D_{4}\right|}{mean\left|D_{4}\right|},$$

$$V_{20}=\frac{std\left|D_{11,10,9}\right|}{mean\left|D_{11,10,9}\right|},\ V_{21}=\frac{std\left|D_{8,7}\right|}{mean\left|D_{8,7}\right|},$$

$$V_{22}=\frac{std\left|D_{6,5,4}\right|}{mean\left|D_{6,5,4}\right|},\ V_{23}=\frac{std\left|D_{3,2,1}\right|}{mean\left|D_{3,2,1}\right|},$$

where $std\left|D_{11}\right|$ is the standard deviation of the eleventh layer of decomposition coefficients, $std\left|D_{11,10,9}\right|$ denotes the standard deviation of the ninth to eleventh layers of decomposition coefficients, and $mean\left|D_{11}\right|$ represents the average of the absolute value of decomposition coefficients.

3. Multi-class SVM Classification Model

The commonly used multi-class SVM classification algorithm is 1-to-1 (1-vs-SVM). When a classification problem is highly complicated, however, training time and computational complexity significantly increase. To illustrate, let us consider k types of samples that need to be classified. To solve this problem, we construct a $k(k-1)/2$ hyper-plane.

To reduce computational complexity, researchers created another classification algorithm, 1-VS-allSVM, this involves hyper-plane classification that distinguishes between one class of samples and the rest of several class samples. Only the $k(k>2)$ hyper-plane can solve the previous problem-- k types of samples that need to be classified. This method is an extension of two types of SVM. The prediction accuracy of the classifier is imperfect because of the huge difference between the number of a single class of samples and the number of the rest of the class samples.

In this paper, we use the BT-SVM method to improve the accuracy and efficiency of the classifier. $k(k>2)$ types of samples require classification. First, we construct $SVM1$ by assigning the 1st sample type as a positive sample and the 2nd, 3rd … kth types as negative samples. We then construct $SVM2$ by denoting the 2nd sample type as a positive sample and the 3rd, 4th … kth types as negative samples. According to the previous method, we construct subsequent classifiers $SVM3\cdots SVM(k-1)$. The number of negative samples gradually decreases; training time also decreases. We choose BT-SVM [10] to classify different scenarios of power quality disturbance. The algorithm is implemented as follows:

1) Divide training sample $C_i(i=1,2,...,k)$ into subsets *T* and *F*, and regard T,F as positive and negative samples, respectively. These samples consist of a classification function $f_i(x)(i=1,2,...,2^N)$.

2) Take $f_i(x)$ as the root node for constructing a binary tree.

3) Repeat steps (1) and (2), then use T as the training data for the left subtree and F to generate a classification function for the right subtree. T is also used to construct the classification function.

4) Repeat step (3) until training sample $C_i(i=1,2,...,k)$ is converted into a group of child nodes;

5) Input testing sample $x_i\in c_i$ to the corresponding binary tree $f_i(x)$.

6) If all testing samples $x_i\in c_i$ belong to the ith sample type, then the classification is completed. The same applies when all testing samples $x_i\in c_i$ are required to traverse from the root node to pass through all the nodes until the category to which the samples belong are identified.

We use different support vector machines to match different scenarios of power quality disturbance. Thus, every support vector machine can solve a particular classification problem and improve accuracy by using training samples.

4. Simulation and Analysis

4.1. Types of Power Quality Disturbances

In the simulation experiment, we construct six types of power disturbance models: voltage sag, voltage swell, voltage interruption, oscillating transient, harmonic, and flicker. The mathematical models are as follows:

1) Normal signal model

$$z(t) = A\sin\omega t \tag{3}$$

where A is the amplitude of a signal, ω denotes the frequency of the signal, and t represents time.

2) Voltage interruption model

$$z(t) = A[1-\alpha(u(t-t_1)-u(t-t_2))]\sin\omega t \tag{4}$$

where α is the amplitude of an additional oscillation signal and $0.9 \le \alpha \le 0.99$; here, T is the period of the signal. We assume that $T \le t_2 - t_1 \le 8T$, the start time of a disturbance is t_1, and the completion time of disturbance is t_2. $u(t)$ is a step function.

3) Voltage sag model

$$z(t) = A[1-\alpha(u(t-t_1)-u(t-t_2))]\sin\omega t \tag{5}$$

where α is the amplitude of the additional oscillation signal and $0.1 \le \alpha \le 0.9$; here, $T \le t_2 - t_1 \le 8T$.

4) Voltage swell model

$$z(t) = A[1+\alpha(u(t-t_1)-u(t-t_2))]\sin\omega t \tag{6}$$

where $0.1 \le \alpha \le 0.5$ and $T \le t_2 - t_1 \le 8T$.

5) Harmonic model

$$\begin{aligned} z(t) = A(&\sin(\omega t) + \alpha_3\sin(3\omega t) + \alpha_5\sin(5\omega t) \\ &+ \alpha_7\sin(7\omega t) + \alpha_{11}\sin(11\omega t)) \end{aligned} \tag{7}$$

where $0.05 \le \alpha_i \le 0.15$.

6) Oscillating transient model

$$\begin{aligned} z(t) = &\sin(\omega t) + \alpha_{osc}\exp(-(t-t_b)/\tau_{osc}) \\ &*\sin(\omega_{nosc}(t-t_b)) \end{aligned} \tag{8}$$

where τ_{osc} is the oscillation constant, ω_{nosc} denotes the oscillation frequency, and α_{osc} is the amplitude of the additional oscillation signal. $\tau_{osc} \in (0.008, 0.04)s$, $\omega_{\text{nosc}} \in (100, 400)Hz$, and $0.1 < \alpha_{osc} < 0.6$.

7) Flicker model

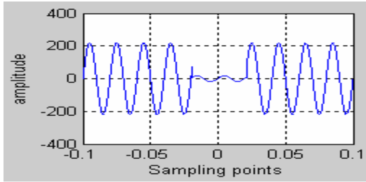
$$z(t) = A(1+\alpha\sin\beta\omega t)\sin\omega t \tag{9}$$

where $0.1 \le \alpha_i \le 0.2$ $0.1 \le \beta \le 0.2$.

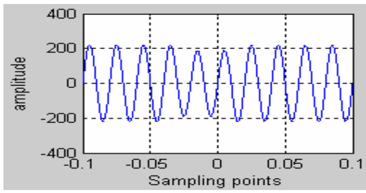
We assume that $A = 220$, $f = 50$, $\omega = 2*3.14*50$, and the rest of the parameters are constrained by their own models. The six types of power transient disturbances are illustrated in **Figure 1**.

4.2. Classification of Power Quality Disturbances

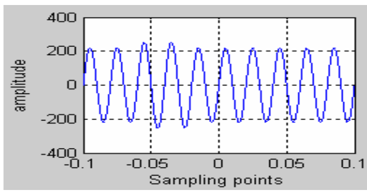
We construct six types of mathematical models to simulate electric power disturbances, namely, voltage interruption, voltage sag, voltage swell, harmonics, oscillating transient, and flicker. We also simulate 600 sets of samples with every type of disturbance scenario. We use a multi-class SVM algorithm to classify the samples. The four different types of kernel functions are the Gaussian radial basis function (GRBF), exponential radial basis function (ERBF), hyperbolic tangent function (HTF), and polynomial function (PF). These are used in SVM algorithms. To obtain an accurate, credible result, we carry



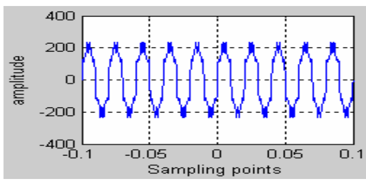
(a) voltage interruption



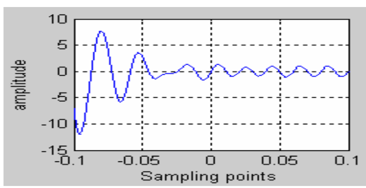
(b) voltage sag



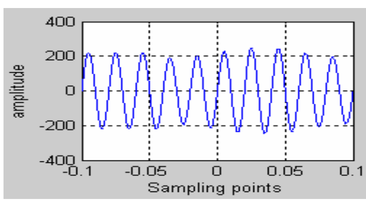
(c) voltage swell



(d) harmonics



(e) oscillating transient



(f) flicker

Figure 1. Oscillogram of various disturbance signals.

out calculations 10 times for every kernel function and adopt 150 or 160 sets of samples each time. The classification results are shown in **Tables 1-6**.

Table 1. Classification results for voltage interruption.

	GRBF	ERBF	HTF	PF 1	PF2
	K=2	K=3	K=4	K=11	K=12
1	150	150	150	73	134
2	150	150	150	135	150
3	150	150	150	77	137
4	150	150	150	143	74
5	150	150	150	67	85
6	150	150	150	114	109
7	150	150	150	75	145
8	150	150	150	100	73
9	150	150	150	107	94
10	150	150	150	71	145
	100%	100%	100%	64.1%	76.4%

Table 2. Classification results for voltage sag.

	GRBF	ERBF	HTF	PF 1	PF2
	K=2	K=3	K=4	K=11	K=12
1	160	160	160	159	129
2	160	160	160	96	78
3	160	160	160	59	119
4	160	160	160	70	95
5	160	160	160	156	130
6	160	160	160	83	104
7	160	160	160	128	100
8	160	160	160	113	79
9	160	160	160	157	127
10	160	160	160	81	69
	100%	100%	100%	68.9%	64.4%

Table 3. Classification results for voltage swell.

	GRBF	ERBF	HTF	PF 1	PF2
	K=2	K=3	K=4	K=11	K=12
1	150	150	150	137	81
2	150	150	150	87	150
3	150	150	150	132	131
4	150	150	150	78	78
5	150	150	150	115	82
6	150	150	150	96	76
7	150	150	150	84	40
8	150	150	150	111	45
9	150	150	150	140	148
10	150	150	150	121	105
	100%	100%	100%	73.4%	62.4%

Table 4. Classification results for harmonics.

	GRBF	ERBF	HTF	PF 1	PF2
	K=2	K=3	K=4	K=11	K=12
1	160	160	160	149	41
2	160	160	160	132	125
3	160	160	160	131	56
4	160	160	160	120	91
5	160	160	160	67	74
6	160	160	160	75	93
7	160	160	160	87	49
8	160	160	160	153	148
9	160	160	160	137	160
10	160	160	160	56	112
	100%	100%	100%	69.2%	69.3%

Table 5. Classification results for f oscillation transient.

	GRBF	ERBF	HTF	PF 1	PF2
	K=2	K=3	K=4	K=11	K=12
1	160	160	160	110	41
2	160	160	160	160	66
3	160	160	160	135	43
4	160	160	160	78	160
5	160	160	160	119	88
6	160	160	160	160	158
7	160	160	160	160	129
8	160	160	160	108	65
9	160	160	160	136	149
10	160	160	160	40	109
	100%	100%	100%	75.4%	63.0%

Table 6. Classification results for oscillation transient.

	GRBF	ERBF	HTF	PF 1	PF2
	K=2	K=3	K=4	K=11	K=12
1	160	160	160	136	85
2	160	160	160	148	53
3	160	160	160	97	137
4	160	160	160	95	70
5	160	160	160	75	157
6	160	160	160	119	113
7	160	160	160	80	81
8	160	160	160	140	88
9	160	160	160	129	160
10	160	160	160	87	72
	100%	100%	100%	69.1%	63.5%

The multi-class SVM classifier with GRBF, ERBF, and HTF are suitable for classifying six types of electric power disturbances. By contrast, PF should not be used to solve such disturbances. As indicated by the results, the choice of kernel function considerably influences the classification results of multi-class SVM.

5. Conclusions

Using wavelet transforms to decompose electric power disturbance signals into 11 layers and extract each layer's detail coefficients as feature vectors can improve the accuracy of classification results. In classifying different types of electric power disturbance signals, the suitable kernel functions for multi-class SVM algorithms are GRBF, ERBF, and HTF. Multi-class SVM classification combined with wavelet transform can be an efficient method for differentiating power quality disturbance signals.

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