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Identification of Multiple Power Quality Disturbances Based on the Improved S-transform and Wavelet Transform Energy Distribution

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Abstract. *To improve the classification accuracy of multiple power quality disturbances, a new feature extraction method for multiple power quality disturbances was proposed based on the S-transform and wavelet transform energy distribution. The S-transform and wavelet transform were used separately to extract the features for power quality disturbances. Features extracted by the above two methods were used as the whole feature to identify the power quality disturbances. The wavelet transform method was used to extract the energy differences between the disturbance signals and standard signal for each layer. The extracted energy differences were used as one part of power quality disturbances features. The S -transform was used to analyze the time-frequency information of the disturbance signals. The time-frequency information was expressed as a matrix in S-transform. We extracted the maximum, minimum, mean, standard deviation, the normalized mean, skewness, and kurtosis from the modulus time-frequency matrix. The extracted features obtained from the S-transform were used as another part of the power quality disturbances features. To improve the performance of S-transform, adjustment factors were introduced to the Gaussian window function to enable a more flexible resolution for the S-transform. We used eleven types of power quality disturbances to test the performance of the proposed method. The simulation results showed that the proposed method had higher classification accuracy.*
Keywords: Power quality disturbance; Wavelet transform; S-transform; Adjustment factor

1. **Introduction.** With the increasing use of the electronic and power electronic equipment, the augmentation of nonlinear, volatility, impact load, the pollution which the power system suffered from is more and more serious. At the same time the development of information technology requires improved power quality. Monitoring and analyzing the power quality is highly important for discovering and managing the power quality. The premise of the power quality analysis is the identification of power quality disturbance (PQD). In the actual power system the power quality disturbance is usually the multiple power quality disturbances and the multiple power quality disturbances is formed by the single disturbances interacting with each other. Traditional methods for identification of single power quality disturbances cannot identify the multiple disturbances well. Therefore, the investigations of multiple power quality disturbances have been conducted [1, 2, 3]. Common single power quality disturbances include: voltage sag, voltage swell, harmonic, voltage interruption, transient oscillation, flicker, etc. Multiple power

quality disturbances mainly include: voltage sag with harmonic, voltage swell with harmonic, flicker with voltage sag, flicker with voltage swell, etc.

The identification of multiple power quality disturbances is composed of two parts: feature extraction and classification. Common feature extraction methods include: Fourier transform(FT), short-time Fourier transform(STFT) [4], wavelet transform(WT) [5, 6] and S-transform(ST) [7, 8, 9]. FT is suitable for analysis of stationary signals, frequency spectrum leakage and fence effect. However, FT is not suitable for analysis of non-stationary signals. To overcome the drawback of the FT, the STFT, which added a window function to the FT, was adopted in [4] to obtain the time-frequency information of the disturbance signals. However, the STFT with a fixed window could not trace the transient and mutation signals. On account of the wavelet transform with a variable resolution, the wavelet transform overcomes the disadvantages of the fixed- width STFT. The wavelet transform operates with high frequency resolution in low frequency and with high time resolution in high frequency and it can be used for multi-scale analysis [5]. The wavelet transform is not well suited for distinguishing the disturbances in the time domain, such as voltage sag/swell. The S-transform can be viewed either as an extension of the WT or a short-time Fourier transform with a variable window. The S-transform introduces a Gaussian window function whose width is decreasing with frequency to provide a frequency-dependent resolution. The S-transform possesses good time-frequency resolution. However, the disadvantages of the S-transform are a large transform module matrix and long computing time.

In this paper, a feature extraction method based on the wavelet energy distribution and improved S-transform for multiple power quality disturbances signals is proposed to solve the problem of low identification accuracy for multiple power quality disturbances. Firstly we used the wavelet transform for a multi-resolution decomposition of the power quality signals. Secondly, we calculated the energy of each layer to obtain the energy distribution by determining the energy difference between the power quality disturbances signal and the standard signal. The energy difference was used as part of the feature vector. At the same time in order to improve the performance of S-transform, we introduced adjustment factors, and used the improved S-transform time-frequency matrix to obtain the maximum, minimum, mean, standard deviation, normalized average, skewness, and kurtosis. We used these values as part of the feature vector. Finally, we used the wavelet energy difference with the seven features extracted from the S-transform as the composite features, and extracted composite features were used as input vectors for a support vector machine (SVM) classifier.

Common classification methods in this field include neural network [10], decision tree [11] and SVM [12]. Neural network has simple structure and strong ability to solve problems. It can deal with the noise data well and it is an important classification method [13]. However, the algorithm has disadvantages, such as the algorithm exists the local optimal problems and poor convergence performance. In addition, training time can be long and over-fitting may occur. Decision tree method attempts to develop classification rules by simulating the human mind, but rules establishment is highly complex. SVM has proven to be an effective algorithm in recent years. It demonstrated good results in solving small sample, nonlinear and high dimensional pattern recognition problems.

2. **Feature extraction using wavelet transform.**

2.1. **Wavelet transform.**
The wavelet transform algorithm is a powerful tool which is used to analyze the time-frequency feature of signals. The width of Gaussian window can be adjusted based on the differences of the signal frequency. The essence of the

wavelet transform is to express a signal function [5] using the wavelet function and wavelet transform coefficient .The wavelet transform expression of the time domain signal $f(x)$ is defined as

$$f(x) = \sum a_{i,j}\psi_{i,j}(x) \tag{1}$$

where i and j are integers, i is the scalability factor, j is the shift factor; $a_{i,j}$ is the discrete wavelet transform coefficient, $\psi_{i,j}(x)$ is the wavelet function. The discrete wavelet transform coefficients can be obtained by formula (2)

$$a_{i,j} = \int_{-\infty}^{+\infty} f(x)\psi_{i,j}(x)dx \tag{2}$$

The wavelet transform function can be obtained by the mother wavelet function for translation and dilating transform.

$$\psi_{i,j}(x) = 2^{-i/2}\psi(2^{-i}x - j) \tag{3}$$

In the case of multi-resolution analysis, the mother wavelet function should meet the two-scale equation:

$$\phi(x) = \sqrt{2}\sum_{k} h(k)\phi(2x - k) \tag{4}$$

$$\psi(x) = \sqrt{2}\sum_{k} g(k)\phi(2x - k) \tag{5}$$

$$g(x) = (-1)^k h(1 - k) \tag{6}$$

Where $\phi(x)$ is the scaling function, h(k) is the coefficient of low-pass filter, and g(k) is the coefficient of the band-pass filter. The mother wavelet function $\psi(x)$ can be created based on the linear combination of the scaling function $\phi(x)$, which is scaled and translated. Its construction process is the designing process of the low pass filter H(w) (the frequency domain representation of h(k)) and the band-pass filter G(w) (the frequency domain representation of g(k)) We choose the DB4 wavelet as the mother wavelet of the Mallet algorithm, and the signal is 8 layers decomposed. The wavelet decomposition coefficient of each layer is used for further processing.

2.2. **Feature extraction using wavelet transform.** According to Parseval theorem, the input signal energy is loaded on the wavelet coefficients [14] , as formula (7)

$$\int [f(t)]^2 = \sum [c_j(k)]^2 + \sum_{x=1:j} \sum_{k} [d_x(k)]^2 \tag{7}$$

Where $f(t)$ is the wavelet signal to be decomposed, $c_j(k)$ is the approximate coefficient of the jth layer, $d_j(k)$ is the detail coefficient of the jth layer. The energy in the approximate coefficient is the base wave energy. The energy in the detail coefficient is the transient energy. A power quality disturbance signal causes an energy change in various frequencies. The transient energy distribution in various frequencies is different when the type of the power quality disturbance signal is changed. Suppose the obtained PQD signal is jth layer decomposed, therefore, the energy distribution of the wavelet transform is defined as:

$$E_{d_j} = \sum_{n} (d_j(n))^2 \tag{8}$$

Where j=1,2..., E_{d_j} is the detail coefficient energy of the jth layer, $d_j(n)$ is the detail coefficient of the jth layer. We used the wavelet transform to decompose the PQD signal into eight layers , and obtained the transient energy E_i i=1,2,...8 of each layer. We minus the transient energy E_i with the standard signal energy E_{ref} , constructed a feature vector using the acquired energy difference $E_i^* = E_i - E_{ref}$. Finally, we got the vector X which can be seen as a part of the feature vector.

$$X = [E_1^*, E_2^*, E_3^*, E_4^*, E_5^*, E_6^*, E_7^*, E_8^*] \tag{9}$$

3. **Feature extraction using S-transform.**

3.1. **S-transform.** The ST proposed by Stockwell et al. [15] can be seen as the phase of the wavelet transform and can be developed from the short-time Fourier transform. The ST of the signal is defined as

$$S(\tau, f) = \int_{-\infty}^{+\infty} h(t) w(\tau - t, f) e^{-i2\pi f t} dt \tag{10}$$

$$w(t, f) = \frac{|f|}{\sqrt{2\pi}} e^{-t^2 f^2/2} \tag{11}$$

$$s(\tau, f) = \int_{-\infty}^{+\infty} h(t) \frac{|f|}{\sqrt{2\pi}} e^{(-\frac{(t-\tau)^2}{\sqrt{2\pi}})} e^{(-i2\pi f t)} dt \tag{12}$$

Where w(t,f) is the Gaussian window function, and $\sigma = \frac{1}{|f|}$ is the width of window. In formula (12), if the frequency f is 0, the value of the S-transform is 0. When the frequency is 0, there is no characteristic quantity, $s(\tau, 0)$ is the time function. At this point, $s(\tau, 0)$ is the mean value of the function $h(t)$.

$$s(\tau, 0) = \lim_{T \to \infty} \frac{1}{T} \int_{-T/2}^{T/2} h(t) dt \tag{13}$$

The ST can be defined as the convolution of two functions

$$s(\tau, f) = p(\tau, f) * g(\tau, f) \tag{14}$$

Where

$$p(\tau, f) = h(\tau) e^{-i2\pi f} \tag{15}$$

And

$$g(\tau, f) = \frac{|f|}{\sqrt{2\pi}} e^{-\frac{\tau^2 f^2}{2}} \tag{16}$$

If $B(a, f)$ is the Fourier transform of $s(\tau, f)$,$P(a, f)$ and $G(a, f)$ are the Fourier transform of $p(\tau, f)$ and $g(\tau, f)$, then

$$B(a, f) = P(a, f) G(a, f) \tag{17}$$

Additionally

$$B(a, f) = H(a + f) e^{-\frac{2\pi^2 a^2}{f^2}} \tag{18}$$

Where $H(a + f)$ is the Fourier transform of formula (16). When $(f \neq 0)$, the Fourier inversion of formula(19) is called the S-transform.

$$S(\tau, f) = \int_{-\infty}^{+\infty} H(a + f) e^{-\frac{2\pi^2 a^2}{f^2}} e^{i2\pi a\tau} da \tag{19}$$

The signal $h(t)$ is sampled at equal interval, T is the time interval, and N is the number of sampling points. Let $f \to n/(NT)$,$\tau \to kT$, and the ST of a discrete time series is given by

$$S(kT, \frac{n}{NT}) = \sum_{m=0}^{N-1} H(\frac{m+n}{NT}) e^{-\frac{2\pi^2 m^2}{n^2}} e^{\frac{j2\pi nk}{N}} \tag{20}$$

$$S(kT, 0) = \frac{1}{N} \sum_{0}^{N-1} h(\frac{m}{NT}) \tag{21}$$

A two-dimensional matrix is obtained by the S-transform. It is a composite time-frequency matrix with rows representing the frequencies and columns representing the time. The modulus matrix of the ST is obtained by calculating absolute values of the elements of the matrix. The columns of the matrix represent the disturbance signal amplitude varying with the frequency at a certain time. The rows of the matrix represent the disturbance signal amplitude varying with the time at a certain frequency.

3.2. **Improved S-transform.** The width of the Gaussian window function is the reciprocal of frequency $\sigma = \frac{1}{|f|}$. For the fixed frequency point f, the width of the window function is fixed. Therefore, the shape of the window function is fixed. The shape of the window function directly affects the resolution of the ST, thus it can affect the feature extraction of the disturbance signal. The power quality disturbances may consist of time, frequency, and multiple time-frequency domain disturbances. Different disturbance signals have different requirements with regard to the resolution of the ST. If the window function is fixed, the resolution is fixed, and it is difficult to attain the feature extraction of diverse disturbance signals simultaneously.

In order to obtain better time-frequency resolution, the adjustment factors λ, p, q are introduced, and the width of the Gaussian window is $\sigma = \frac{\lambda}{q+|f|^p}$. According to the frequency distribution of the signals, the Gaussian window width is adjusted based on the frequency, so that the Gaussian window width changes at the multi-level with the frequency. The parameter λ ensures that the Gaussian window width is inversely proportional to the frequency, p has a translational relationship with f, and q has an exponential relationship with f. when p and q are constants, by adjusting the value of parameter λ , the ratio of the inversely proportional relationship between the width of the Gaussian window and the frequency varies. When $\lambda > 1$, the ratio is lower, the time resolution is lower, but the frequency resolution increases. When $0 < \lambda < 1$, the ratio of the width of window proportional to the frequency is higher, and the time resolution increases. When the parameters p, q changed the same value, the impact of p on the window function is greater than q. The two adjustment factors can adjust the resolution of ST meticulously. Based on the Heisenberg principle, time resolution and frequency resolution cannot improve simultaneously. When p and q increase, the amplitude of the window function increases. The attenuation speed is faster and the time resolution increases, but the frequency resolution decreases. On the contrary, when p and q decrease, the amplitude and time resolution decreases and the frequency resolution increases. Therefore, when $\lambda > 1$ and p, q decrease, the frequency resolution of the improved ST is high. When $0 < \lambda < 1$ and p, q increase, the time resolution is high.

At the same time, for a non-stationary signal, the time-frequency distribution characteristic of the different frequency components is different when the frequency components are distorted. The low-frequency part of signal changes in a relatively stable manner and the high-frequency part of signal changes in a relatively intense manner [16]. For the same signal in different spectrum the intensity of change differs, therefore, the signal frequency spectrum is divided into low, intermediate, and high frequency. The width adjustment factor is determined respectively based on the different resolutions in the different frequency domains. At this point, the improved S-transform is defined as

$$S(\tau, f) = \int_{-\infty}^{+\infty} h(t) \frac{q + f^p}{\sqrt{2\pi}\lambda} e^{-\frac{(t-\tau)^2[q+f^p]^2}{2\lambda^2}} e^{-\frac{i2\pi(q+f^p)}{\lambda}} dt \tag{22}$$

After the improved S-transform modulus matrix is obtained, the effective features which are extracted from the rich information in the S-transform modulus matrix are classified. The experimental results suggest that the classification accuracy is improved significantly. Figure 1 and Figure 2 show the maximum of the row vector after the S-transform and the improved S-transform. Figure 3 and Figure 4 show the power frequency amplitude curves of the S-transform and the improved S-transform. The results indicate that the improved S-transform can detect some harmonic ingredient but the S-transform cannot detect it (Fig1,Fig2), and the start and ending time of the swell are more obvious for the improved S-transform (Fig3,Fig4).

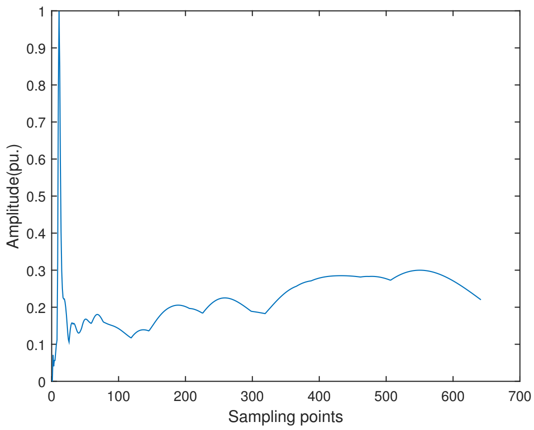

FIGURE 1. The Row Vector Maximum of S-transform

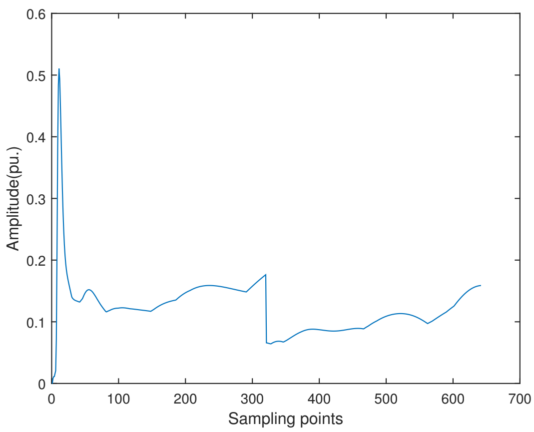

FIGURE 2. The Row Vector Maximum of improved S-transform

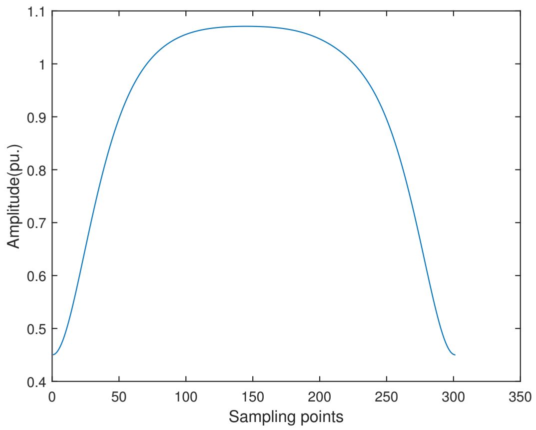

Figure 3. The Power Frequency Amplitude Curve Of S-transform

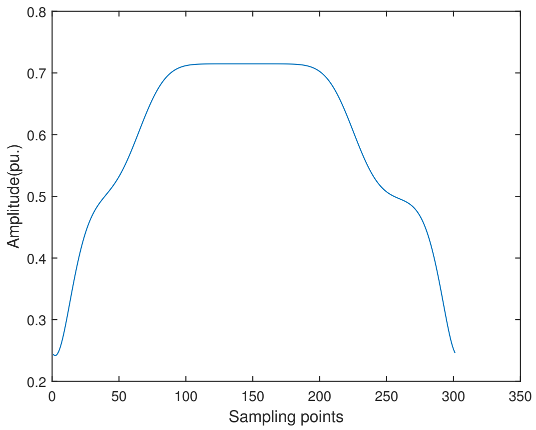

Figure 4. The Power Frequency Amplitude Curve Of improved S-transform

3.3. **Feature extraction using improved S-transform.** We extracted features from time, frequency and amplitude. The seven features(F1-F7) that we extracted from the improved S-transform modulus matrix were as follows:.
F1: max of the maximum of each column in the modulus matrix
F2: min of the maximum of each column in the modulus matrix
F3: mean of the maximum of each column in the modulus matrix
F4: standard deviation of the maximum of each column in the modulus matrix
F5: normalized average of each column in the modulus matrix
F6: the skewness of the curve of maximum frequency
F7: the kurtosis of the curve of maximum frequency
When the type of power quality disturbance is large, it was difficult to establish a suitable rule to distinguish all the disturbances with only one type of feature. Multiple features were obtained by combining the features extracted by the ST with the features extracted by the wavelet transform.

4. **Identifying multiple power quality disturbances.** This paper aimed to identify power quality disturbances for seven single disturbances (voltage swell, voltage sag, harmonic, voltage interruption, transient oscillation, transient pulse, voltage flicker) and four multiple disturbances (swell with harmonic, sag with harmonic, flicker with swell, flicker

with sag). [17] described the mathematical model for the eleven power quality disturbances. The identification of multiple power quality disturbances was divided into two steps: feature extraction and classification.

The S-transform and the wavelet transform were used separately to extract features for power quality disturbances. The wavelet transform was used to dispose the eleven power quality disturbance signals. We used the DB4 wavelet as the mother wavelet for the Mallat algorithm and decomposed the signal into eight layers. We extracted the decomposed wavelet coefficient for each layer, using the parseval theorem to calculate the wavelet energy for each layer, and calculated the energy differences between the power quality signal and the standard signal. The eight energy differences were used as part of the characteristic vectors. The S-transform was used to extract features. In order to obtain the more flexible time-frequency resolution, the adjustment factors λ, p, q were introduced to improve the S-transform. This changed the rate which the width of Gaussian window varied with the frequency at the multilevel. The change in intensity of the power quality disturbance at different frequencies is different, and in order to solve this problem, the spectrum of signals was divided into three frequency areas. The width factor of the window function was defined separately for the different frequency areas in order to identify different disturbance signals. The improved S-transform was used to dispose the power quality disturbances. We extracted the maximum, minimum, mean, standard deviation, the normalized average, skewness, kurtosis of the modulus time-frequency matrix. The seven features were used as part of the characteristic vector. Features extracted with the above two methods were used as the composite feature of power quality disturbances. Then the features were normalized for processing and were classified in the next step.

SVM was used for classification. A portion of the normalized data was used as training samples. The training samples was trained to establish the classification model. The remaining data were used as testing samples to obtain the classification accuracy. Therefore, we can achieve the accurate identification of the multiple power quality disturbances.

5. **Simulation experiment and analysis.** We classified the eleven power quality disturbance signals, then, put the features into the support vector machine classifier to verify the effectiveness of the disturbance identification method. 200 simulated events of each disturbance were generated according to [17]. In order to create different disturbance cases, the parameters for each different disturbance, such as disturbance amplitude, starting and end time, duration were changed randomly as described in [17]. We used 80 training samples and 120 test samples. During processing, the fundamental frequency was 50 HZ. There were 1281 sampling points per cycle. The width of the signal was ten cycles.Table 1 shows the classification accuracy of the eleven power quality disturbance signals for the extracted feature vectors for the S-transform, improved S-transform, and the improved S-transform with wavelet transform.

Table 1 shows that: the classification accuracy of the method using the improved S-transform with wavelet transform was higher overall compared to the other two methods, and the classification accuracy of nearly every disturbance type was also higher. Due to the voltage swell, sag, interruption and flicker at the amplitude characteristics change significantly. The classification accuracy of the three methods for these four disturbances was very high. The fundamental frequency property of the harmonic is stable. The high-frequency portion influenced by harmonic changed significantly. For the improved S-transform, the adjustment factors were defined separately for different frequency areas, and this helped with the identification of the harmonic. Therefore, the classification accuracy for the improved S-transform and the wavelet transform with improved S-transform was clearly higher than that for the S-transform. The results for the transient pulse were

Table 1. Classification accuracy of various disturbance signals

Disturbance types	Classification accuracy (in %)		
	S-transform	Improved S-transform	Wavelet transform and improved S-transform
Average classification accuracy	77.7273	92.2727	99.697
Swell	100	100	100
Sag	100	100	100
Interruption	100	100	100
Harmonic	50.8333	72.5	100
Transient pulse	59.1667	91.6667	99.1667
Transient oscillation	95	68.3333	100
Flicker	100	100	97.5
Swell with harmonic	69.1667	93.3333	100
Sag with harmonic	60	98.3333	100
Flicker with swell	63.3335	91.6667	100
Flicker with sag	57.5	99.1667	100

similar to that of the harmonic. The signal distortion of the transient oscillation was mainly reflected in the high-frequency part. The frequency range of the distortion was higher for the transient oscillation than for the harmonic, the harmonic with sag, and the harmonic with swell. The width adjustment factor was set respectively for low, intermediate, and high frequency. The adjustment factor was the same in the high-frequency part. However, the distortion of these four types of disturbances was in the high-frequency part. Therefore, the classification accuracy of the improved S-transform was lower for the transient oscillation than the S-transform. However, the classification accuracy of the wavelet transform with improved S-transform was high. The flicker is amplitude modulated wave and low frequency, time-varying, non-stable disturbance signal. Because of the variation of the flicker amplitude modulated wave , the time-frequecy property of flicker has high requirement of the frequency-selection characteristic with the wavelet function . Flicker needs different values of the DB wavelet to decmpose it, or it will generate spectrum leakage. In this paper, we choose DB4 wavelet to decompose the power quality disturbance signals, then extracted the wavelet energy differences as the feature vectors . We have not used the different values of DB wavelet, therefore it leads to decline of the classification accuracy for flicker.

The swell with harmonic, sag with harmonic, flicker with swell, and flicker with sag retained the variation characteristics of the harmonic and flicker, and the amplitude of the sag and swell variation was clear and easy to distinguish. The promotion of the classification accuracy were apparent for the four multiple power quality disturbance. This indicated that the identification method proposed in this paper could extract features effectively and resulted in high classification accuracy for the common multiple power quality disturbances. It was concluded that the method was feasible for the intended application.

6. **Conclusion.** This paper has presented a new approach for identification of multiple power quality disturbance signals using the wavelet energy distribution and improved S-transform. The improved S-transform resulted in better differentiation of the signals features and in improved classification accuracy. The method was used to develop a composite feature vector which was extracted using the wavelet transform and improved S-transform, followed by a classification using the SVM. The average classification accuracy was higher for the proposed method than the other two methods.

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