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Gas Turbine Blades Fault Diagnosis Method with EMD Energy Entropy and Related Vector Machine

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Abstract. *In this paper, we use the temperature of the gas turbine blades for failure analysis, because in the real life it is difficult for us to measure the failure temperature data of the gas turbine blade, and therefore we require a basic understanding of gas turbine blade structure and working principle to simulate the fault data of the gas turbine blade. Then do the gas turbine fault diagnosis of turbine blades based on empirical mode decomposition and relevance vector machine. First decompose failure non-stationary signals into several stationary signals by EMD method, which is the sum of intrinsic mode function. When the turbine blade is broken down, the energy of the signal in different frequency bands change, therefore, its energy entropy can be calculated to determine whether it is the failure.*
Keywords: Gas turbine; Turbine blade; Fault diagnosis; Relevance Vector Machine; Empirical Mode Decomposition.

1. **Introduction.** Gas turbine[1] is an advanced power machinery equipment, which occupies an important strategic position in shipbuilding, aerospace and other modern industrialized areas. As a high-tech technology-intensive equipment, gas turbine technology represents a country's technological strength. Because the gas turbine technology is more complexity and advanced and the working environment is very bad, it is particularly prone to failure. The traditional periodic maintenance program is not only a waste of time even more impact on the overall life of the machine, preferably a technology which can be capable of monitoring gas turbine, and timely maintenance and repair of machines and increase the efficiency of the machine is needed. So gas turbine engine fault diagnosis technology has become a hot research[2][3]. Gas turbine fault diagnosis[4][5] technology is still in the theoretical stage, but many countries have invested a lot of human and material resources in this area. The turbine blades as the main components of the gas turbine, is the main reason for the occurrence of the fault, and thus detection and fault diagnosis through the turbine blades is one of the main research directions. How to extract fault characteristics from non-stationary temperature signals is the key of gas turbine blade failure diagnosis techniques. The traditional method of dealing with non-stationary signal is Fourier analysis and wavelet transform[6][7]. Since the Fourier analysis method is based on stationary signals, for non-stationary signals it can only give a total average effect. When it has a high resolution in the time domain, the main lobe of the spectrum due to its wider inevitably lead to the frequency domain resolution decreasing. Later scholars have proposed a method of wavelet transform to make up for the shortcomings

of this method of Fourier analysis[8][9]. But the selection of the wavelet basis is before wavelet transform analysis, which cannot guarantee that the selected wavelet basis is the optimal wavelet basis, that is to say it has no self-adaptive wavelet analysis[10]. Chinese-American Dr. Huang E et al[11] proposed empirical mode decomposition method for the analysis of non-stationary signals, and its main function is to decompose non-stationary signals into the sum of a series of intrinsic mode functions. Because the base of EMD to be taken directly from the signals, and each IMF component is determined by the signal itself, with fully adaptive, the signal analysis is more flexible. EMD is well suited for processing non-stationary signals, so it is used to process the temperature signal of the turbine blades[12]. When turbine blade is broken down, the signal energy in different frequency bands changes, so by calculating the energy entropy of the signal we can determine whether it is broken. Then the IMF components containing fault information are put in relevance vector machine, the fault types of the turbine blades are put out. In this paper, the results will be compared with that on support vector machines, and we can see the advantages of relevance vector machine in the small samples, less classification situations.

2. **EMD Method.** In the EMD transform, in order to calculate the instantaneous frequency, we define the intrinsic mode function, which is a class signal to meet the physical interpretation of a single component signal. At each moment the intrinsic mode include only a single frequency component, so the instantaneous frequency has a physical meaning. Intuitively, the intrinsic mode functions have the same number of extreme points and zero-crossing points, and its waveform is similar to a new signal that a standard sinusoidal signal obtain by AM and FM. An intrinsic mode function must be met the following two conditions:

1. in the whole data segment, the number of extreme points and the number of zero crossings must be equal or differ at most not more than one;
2. at any time, the average of the upper envelope formed by a local maximum point[13] and the lower envelope formed by the local minimum point is zero, that is, the upper envelope and the lower envelope are the local symmetry to the axis.

The first condition is similar to traditional narrowband requirements of Gaussian normal stationary process, and the second condition is to ensure that the instantaneous frequency determined by the intrinsic mode function is meaningful. Based on this definition, the intrinsic mode function reflects the inherent volatility of the internal signals[14]. In each of its cycle, it only contains a volatile modal, so multiple fluctuation modal aliasing phenomenons does not exist. A complex signal is decomposed into a number of intrinsic mode functions by EMD method and that it is based on a fundamental assumption: Any complicated is composed by a number of different intrinsic mode functions; Each intrinsic mode functions either linear or non-linear, stationary or non-stationary, all have the same number of extreme points and zero crossing, only one extreme point between two adjacent zero-crossings, and Upper and lower envelope are on the local symmetry axis; Any two of the modes are overlap, they a complex signal is formed. On the basis of this hypothesis, by the EMD measure any signal can be decomposed by the following steps[15].

1. First, find all the local extreme point of the signal, and then take all of the local maxima obtaining the upper envelope. Then all the local minimum points are connected to form the lower envelope in the same way. All data points should be included in the upper and lower envelope[16]. The average of the upper and lower envelope is m_1 . Then,

$$x(t) - m_1 = h_1 \tag{1}$$

If h_1 satisfies the conditions of the IMF, h_1 is the first component of IMF.

2. If h_1 does not satisfy the condition of IMF, put h_1 as the original signal, then repeat steps (1).Get the average of the upper and lower envelope m_1 .Then judge whether $h_1 1 = h_1 - m_1 1$ meet the conditions of IMF. If it is not satisfied, then continue cycling k times to obtain $h_{1(k-1)} - m_{1k} = h_{1k}$, until h_{1k} meets the IMF conditions. Make $c_1 = h_{1k}$, then c_1 is the first signal component which satisfies the conditions for IMF.
3. Separated c_1 from x(t) to get:

$$r_1 = x(t) - c_1 \tag{2}$$

Make r_1 as the original signal to continue repeating steps (1), (2) to obtain a second component c_2 which satisfies the conditions of IMF. Repeated n times to produce n components that satisfy the conditions of IMF. Then,

$$\begin{cases} r_1 - c_2 = r_2 \\ \cdots\cdots \\ r_{n-1} - c_n = r_n \end{cases} \tag{3}$$

Until a monotonic function of r_n is get, loop ends. Thus by the formula (2), (3) to give:

$$x(t) = \sum_{i=1}^{n} c_i + r_n \tag{4}$$

The formula (4) shows that the signal can be decomposed into n IMFs and a residual component. Intrinsic mode components represent different components of the signal from high to low frequency, and frequency components contained in each band is not the same, which will change with changes in temperature signals. The residual function represents the overall trend of the signal.

3. **The Energy Entropy Selecting a Template.** When the turbine blade goes wrong, the frequency of the temperature signal will change, and correspondingly, the energy distribution of the fault temperature signal will change, so after calculating the energy of each component of IMFs with EMD, it is necessary to introduce the concept of the entropy energy. After getting n IMFs with EMD, we can calculate the energy of the turbine blade temperature signal. We call them $E_1, E_2, E_3, ..., E_n$.The residual component is too little to ignore. Since the bands of each IMF components with EMD are different, that means each component is orthogonal. So all the energy of the IMFs should be equal to that of the original temperature signal. (Assume the energy of the residual component is negligible). So we give the definition of EMD energy entropy[17].

$$H_{EN} = -\sum_{i=1}^{n} p_i \log p_i \tag{5}$$

In the above formula, $p_i = \frac{E_i}{E}$ represents the proportion of $i-th$ intrinsic mode functions in the total energy.

According to the above method, we calculate the energy entropy in three different conditions: normal state, the overall high temperature state, the local high temperature state.

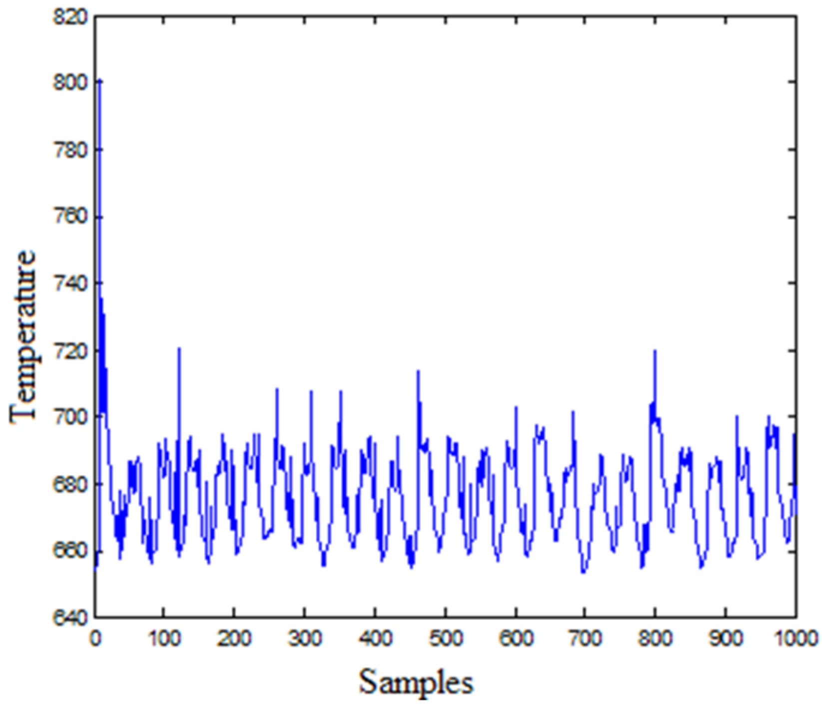

Figure 1. Temperature fault signal at a certain conditions

Table 1. EMD energy entropy of turbine blades in different conditions and different working conditions

Working conditions	**Conditions & Energy entropy**		
	0.6	**0.8**	**1.0**
Normal state	1.5506	1.5524	1.5536
The overall high temperature state	1.4189	1.4193	1.4205
The local high temperature state	1.1785	1.1792	1.1804

From the above table we can see that the energy entropy in different conditions but a working state is nearly equal, and the energy entropy in different working states is different. In reality, when the turbine blades are working, it is difficult for us to identify what states exactly they are in. But from the above calculation we can see that the energy entropy is substantially constant no matter what states they are in. So we can make the energy as feature vectors of fault diagnosis[18]. The energy entropy of the turbine blades under normal state should be the biggest, because under normal state the temperature distribution of the turbine blade is relative to the average. Therefore, the energy entropy can be used to determine the working status of the turbine blade.

4. **Relevance Vector Machine Algorithm.** Relevance vector[19] classification follows an essentially identical framework as detailed for regression in the previous section. We simply adapt the target conditional distribution(likelihood function) and the link function to account for the change in the target quantities. As a consequence, we must introduce an additional approximation step in the algorithm[20].

For two-class classification, it is desired to predict the posterior probability of membership of one of the classes given the input x. We follow statistical convention and generalize

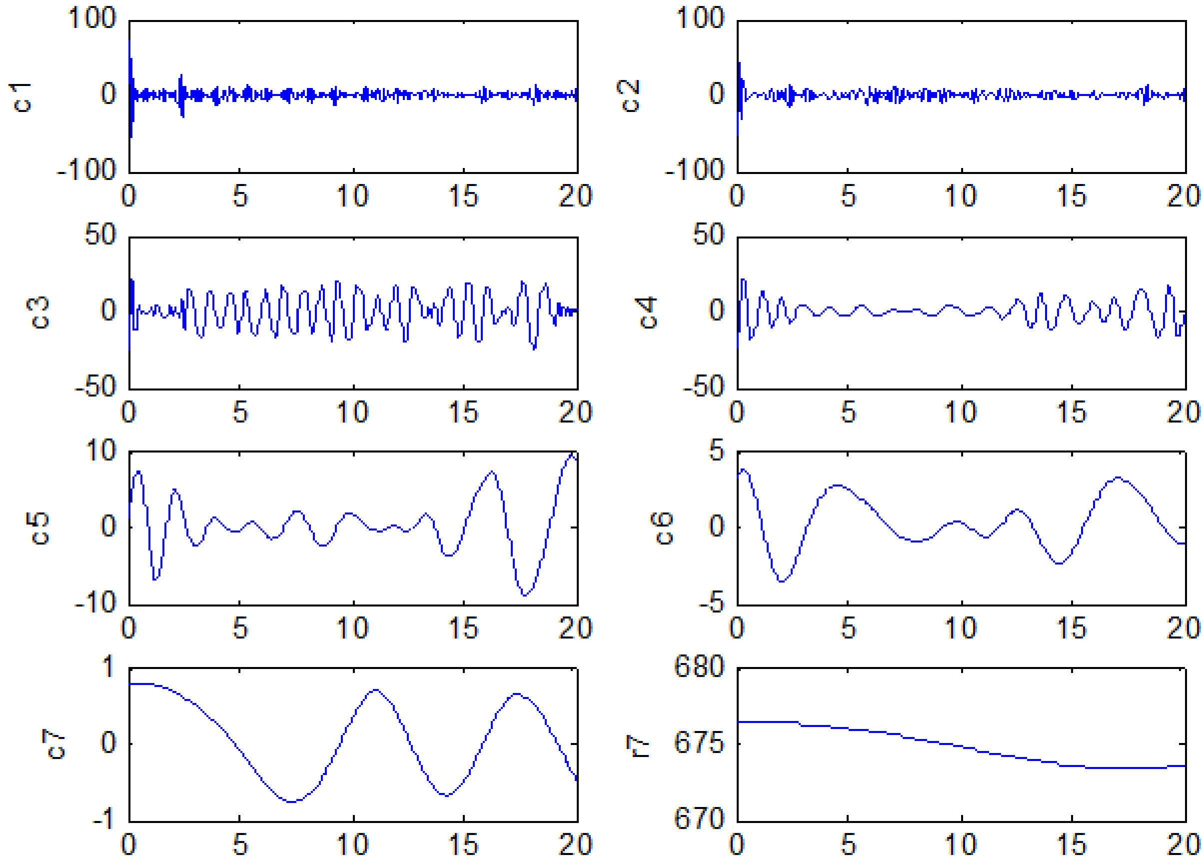

FIGURE 2. EMD decomposition of temperature fault signals

the linear model by applying the logistic sigmoid link function $\sigma(y) = \frac{1}{1+e^{-y}}$to $y(x)$and, adopting the Bernoulli distribution for$p(t|x)$, we write the likelihood as:

$$p(t|\omega) = \prod_{n=1}^{N} \sigma\{y(x_n;\omega)\}^{t_n}[1 - \sigma\{y(x_n;\omega)\}]^{1-t_n} \tag{6}$$

where, following from the probabilistic specification, the targets $t_n \in \{0, 1\}$. Note that there is no noise variance here. However, unlike the regression case, we cannot integrate out the weights analytically, and so are denied closed-form expressions for either the weight posterior $p(\omega|t, \alpha)$ or the marginal likelihood $p(t|\alpha)$. We thus choose to utilize the following approximation procedure, as used by MacKay(1992b), which is based on Laplace's method:

1. For the current, fixed, values of α, the most probable weights ω_{MP} are found, giving the location of the mode of the posterior distribution.

   Since $p(\omega|t, \alpha) \propto p(t|\omega)p(\omega|\alpha)$, this is equivalent to finding the maximum, over ω, of

$$\log\{p(t|\omega)p(\omega|\alpha)\} = \sum_{n=1}^{N} [t_n \log y_n + (1 - t_n)log(1 - y_n)] - \frac{1}{2}\omega^T A\omega \tag{7}$$

   with $y_n = \sigma\{y(x_n;\omega)\}$. This is a standard procedure, since (7) is a penalized (regularized) logistic log-likelihood function, and necessitates iterative maximization.

Second-order Newton methods may be effectively applied, since the Hessian of (7), required next in step 2, is explicitly computed. We adapted the efficient iteratively-reweighted least-squares algorithm [21](e.g. Nabney, 1999) to find ω_{MP}.

2. Laplace's method is simply a quadratic approximation to the log-posterior around its mode. The quantity (2) is differentiated twice to give:

$$\nabla_\omega \nabla_\omega \operatorname{logp}(\omega|t,\alpha)|_{\omega_{MP}} = (\phi^T B\phi + A) \tag{8}$$

where $B = diag(\beta_1, \beta_2 \ldots, \beta_N)$ is a diagonal matrix with $\beta_n = \sigma\{y(x_{n)}\}[1 - \sigma\{y(x_{n)}\}]$. This is then negated and inverted to give the covariance $\sum$ for a Gaussian approximation to the posterior over weights cantered at ω_{MP}.

3. Using the statistics $\sum$ and ω_{MP} (in place of μ) of the Gaussian approximation, the hyper parameters α are updated using $\alpha_i^{new} = \frac{\gamma_i}{\mu_i^2}$ in identical fashion to the regression case[22]. At the mode of $p(\omega|t,\alpha)$ using (8) and the fact that $\nabla_\omega \operatorname{logp}(\omega|t,\alpha)|\omega_{MP} = 0$ we can write:

$$\sum = (\phi^T B\phi + A)^{-1} \tag{9}$$

$$\omega_{MP} = \sum \phi^T B\text{t} \tag{10}$$

These equations are equivalent to the solution to a generalized least squares problem(e.g. Mardia et al., 1979, p.172) . Compared with $\sum = (\sigma^{-2}\phi^T\phi + A)^{-1}$ and $\mu = \sigma^{-2}\sum \phi^T t$, it can be seen that the Laplace approximation effectively maps the classification problem to a regression one with data-dependent (heteroscedastic) noise, with the inverse noise variance for ε_n given by $\beta_n = \sigma\{y(x_{n)}\}[1 - \sigma\{y(x_{n)}\}]$.

5. **Simulation with Matlab.** Firstly decompose fault signal with EMD, and make IMF components as the input of relevant vector machine. Specific process is as follows:

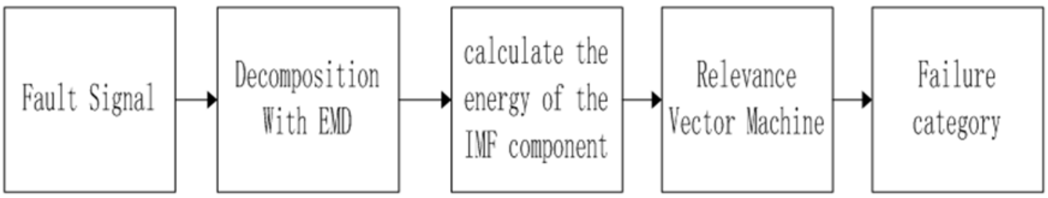

FIGURE 3. Troubleshooting flowchart based on EMD energy entropy and relevance vector machine algorithm

Specific steps are as follows:

1. Analog 20 groups of data in the three states: normal state, the overall high temperature state, the local high temperature state.
2. Get IMF component of for each set of data by EMD. Because IMF data for each component is different, we choose the first six IMF components for the study group[23]
3. Then calculate the energy of the first n IMF components

$$E_i = \int_{-\infty}^{+\infty} |c_i(t)|^2 dt \ (i = 1, 2, ..., n) \tag{11}$$

4. Construct the feature vectors:

$$T = [E_1, E_2, \cdots, E_n] \tag{12}$$

5. To facilitate processing normalize T:

$$E = \left(\sum_{i=1}^{n} |E_i|^2 \right)^{1/2} \tag{13}$$

Then,

$$T' = [E_1/E, E_2/E, \cdots, E_n/E] \tag{14}$$

And T' can be used as input of related vector machine

6. Select classifier. There are only three types of turbine blade failure, so we can use "one on one" approach to classification in this multi-classification recognition accuracy directly[24].
7. Select the kernel function. Select the most appropriate kernel function RBF kernel:

$$K(x, z) = exp(-\frac{||x - z||^2}{\sigma^2}) \tag{15}$$

6. **Results and analysis.** The energy component of the IMF with EMD decomposition is as following Table 2.(All is not listed because of space reasons.) In the experiment, former four groups of IMF components are selected as the feature vectors. The number of the IMF components of failure temperature signal is greater than 4. Randomly select the 48 groups as training samples, and the rest 12 groups as a test sample.

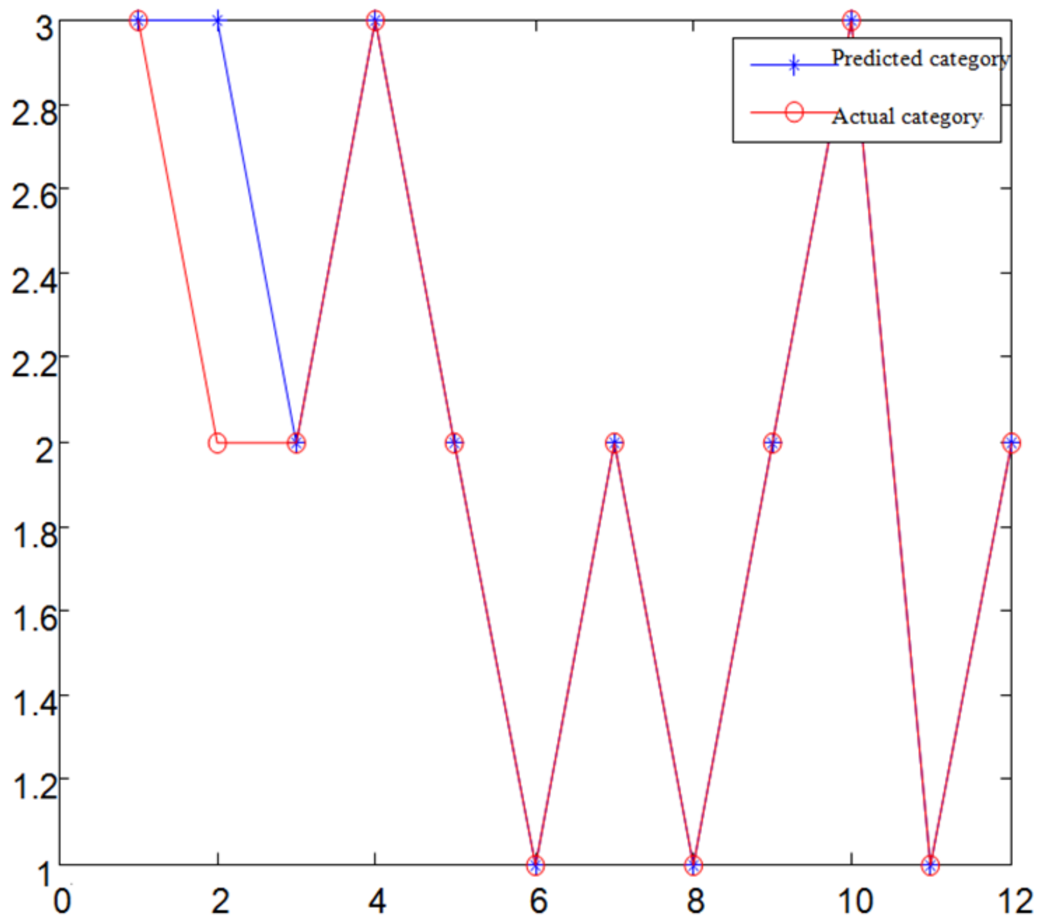

Figure 4. Test results on related vector machine

Table 2. Feature vecters of the turbine blades under each state

State	NO.	Feature vectors $\frac{E_1}{E}$	$\frac{E_2}{E}$	$\frac{E_3}{E}$	$\frac{E_4}{E}$
Normal	1	0.8185	0.5441	0.178	0.0422
	2	0.7635	0.6371	0.0986	0.0347
	3	0.7402	0.6649	0.0961	0.0218
	4	0.7643	0.6307	0.1282	0.0375
	5	0.7388	0.6673	0.0905	0.0206
	6	0.7782	0.6135	0.1247	0.0472
The local high temperature	1	0.9218	0.3551	0.1493	0.0408
	2	0.9339	0.332	0.1265	0.0338
	3	0.9256	0.362	0.1033	0.0352
	4	0.9273	0.3411	0.1495	0.0341
	5	0.9318	0.3385	0.1227	0.0421
	6	0.9082	0.393	0.1401	0.0289
The overall high temperature	1	0.9019	0.4246	0.0729	0.0273
	2	0.9015	0.4203	0.0981	0.0275
	3	0.9102	0.4035	0.0904	0.0215
	4	0.8739	0.4663	0.1301	0.0372
	5	0.8923	0.4409	0.091	0.0282
	6	0.9138	0.3953	0.0892	0.0243

The results obtained are shown in Figure 4. From Figure 4,We can see the correct rate on relevance vector machine algorithm for the turbine blades fault diagnosis is very high. So the turbine blade failure diagnosis method based on EMD energy entropy and relevance vector machine algorithm is feasible.

7. **Conclusion.** In this paper, the turbine blade failure signal is decomposed into IMF component, and then we calculate the energy and normalize it, which is regard as the feature vector of the relevance vector machine. Get the good classification results on RVM. The conclusions we get is as following:

1. EMD as a signal analysis method is adaptive, which can well deal with the non-linear and non-stationary signals.
2. Good turbine blade failure classifications can be achieved by EMD energy entropy and relevance vector machine.

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