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基于提升小波包的离心泵故障诊断方法

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摘　要: 为准确诊断离心泵的振动故障,提出了基于提升小波包和相关向量机的离心泵振动故障诊断方法。首先通过提升小波包方法快速提取各状态振动信号的分解系数能量、时域统计参数作为特征量。针对支持向量机稀疏性不高而导致诊断速度慢的问题,利用相关向量机实现分类诊断。研究结果表明,该方法能够有效地诊断离心泵的振动故障,诊断率达 95.5%; 与其它算法相比,测试时间短,只有 0.022 s,更适合在线诊断。

关 键 词: 离心泵; 故障诊断; 提升小波包; 相关向量机

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引　言

离心泵在旋转过程中所产生的振动强弱及所包含频率成分与故障的类型、程度、部位等有着密切的联系,利用振动进行故障监测诊断是目前应用最广泛的方法[1]。小波包变换以其优异的时频分辨特性被用来作为提取故障特征的一种常用方法[2~4]。

提升小波变换继承了经典小波多分辨率特性,具有变换在时域进行,可以原位运算,占用空间小,易于逆变换的特点[5~6]。提升小波变换还是一种柔性的小波变换方法,同经典小波变换相比,计算方法更简单,而且适合于自适应、非线性变换。同样数据长度下,提升小波的变换速度至少比经典小波快一倍[7],因此更适合信号的在线处理。在齿轮、轴承故障诊断中已有应用[6~8],在离心泵振动信号分析中还未见报道。

本研究采用提升小波包对振动信号进行分解并重构,提取频带归一化能量特征建立特征向量,并作为相关向量机的输入样本,通过典型故障样本的训练形成一种新的诊断方法。

1　提升小波包故障特征提取

1.1　提升小波包原理

采用插补细分原理设计预测器和更新器,所获得双正交的小波函数和尺度函数是对称的、紧支撑的,并具有冲击衰减形状,能较好地与振动信号匹配,它们具有良好的紧支性和广义线性相位,变换时可以有效地抑制相位失真,这种提升小波记为$(N,\bar{N})$,其中 N、$\bar{N}$分别为预测器和更新器的长度。

设离散信号为 $x[i]$($i=1,2,\cdots 2^M, M\in Z^+$),依据提升小波变换原理,以及小波包变换定义,插补细分提升小波$(N,\bar{N})$的提升小波包变换过程分为分解步骤和重构步骤,具体如下:

(1) 分裂。将第(j,n)($j=0,1,\cdots,l$; $n=0,1,\cdots,2^{j-1}$)节点系数 d_n^j 奇偶分裂为 d_{no}^j, d_{ne}^j。

(2) 预测。由式(1)得到第$(j+1,2n+1)$节点系数为:

$$d_{2n+1}^{j+1}[k]=d_{no}^j[k]-\sum_{i=1}^{N}P[l]d_{ne}^j[k+l-N] \quad (1)$$

$$k=1,2,\cdots,2^{M-(j+1)}$$

式中: $d_{no}^j[k]$—第(j,n)节点的第 k 个奇系数; $P[l]$—预测器系数; $d_{ne}^j[k+l-N]$—(j,n)节点的第$(k+l-N)$个偶系数。

(3) 更新。由式(2)得到第$(j+1,2n+1)$节点系数为:

$$d_{2n}^{j+1}[k]=d_{ne}^j[k]-\sum_{i=1}^{\bar{N}}U[l]d_{2n+1}^{j+1}[k+l-\bar{N}] \quad (2)$$

式中: $U[l]$—更新器系数。

重构步骤如下:

(1) 反更新。由$(j+1,2n)$,$(j+1,2n+1)$节点稀疏求取(j,n)节点的偶系数为:

$$d_{ne}^j[k]=d_{2n}^j[k]-\sum_{i=1}^{\bar{N}}U[l]d_{2n+1}^{j+1}[k+l-\bar{N}] \quad (3)$$

(2) 反预测。由$(j+1,2n+1)$节点的系数和(j,n)节点的偶系数求取(j,n)节点的奇系数为:

$$d_{no}^j[k]=d_{2n+1}^{j+1}[k]+\sum_{i=1}^{N}P[l]d_{ne}^j[k+l-N] \quad (4)$$

$$d_{no}^j[k]=d_{2n+1}^{j+1}[k]+\sum_{i=1}^{N}P[l]d_{ne}^j[k+l-N] \quad (5)$$

(3) 合并。将奇偶系数 d_{no}^j、d_{ne}^j合并到第(j,n)

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节点的系数 d_n^j。

提升小波包一阶分解与重构过程如图 1 所示，其中，P 为预测器，U 为更新器。

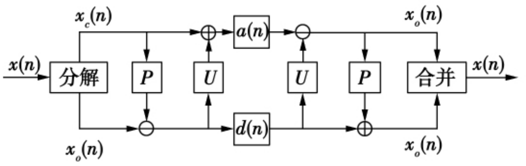

图 1　提升小波算法的分解与重构框图

Fig. 1 Decomposition and restructuring block diagram of the lifting wavelet algorithm

提升小波包变换结构可以用与其对应的小波包树表示。3 层小波包分解树如图 2 所示。

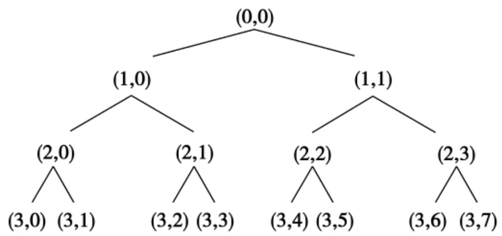

图 2　3 层提升小波包分解的树结构

Fig. 2 Decomposition tree structure of the lifting wavelet package in three layers

1.2　离心泵故障特征提取

小波包分解不仅能对低频部分分解，还可对高频部分进行分解，因此可提供信号更多的时频信息。偏度系数和峭度系数是信号时间序列分布特性的统计量，若离心泵发生故障，则数据的分布特性也将发生变化。故障振动信号与正常系统的振动信号相比，相同频带内信号的能量会有较大差别，故障信号的能量在某些频段内会减少，而在另外一些频带内会增加。因此，在信号各频率成分的能量中包含着丰富的故障信息，综合以上，本研究采用各提升小波包分解各个终节点系数的能量、偏度系数、峭度系数等特征参数作为离心泵振动故障的特征向量 T，则：

$$T = [g_{11}, \cdots, g_{r1}, g_{12}, \cdots g_{r2}, E_1/E, \cdots, E_r/E] \quad (6)$$

式中：g_{r1}—偏度系数；g_{r2}—峭度系数；E_r—能量，$r = 1, 2, \cdots, 2^j$。具体计算式为：

$$g_{r1} = \frac{1}{N}\sum_{k=1}^{N}\left[\frac{d_r(k) - u}{\sigma}\right]^3 = \frac{E\,[d_r(k) - u]^3}{\sigma^3} \quad (7)$$

$$g_{r2} = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{d_r(k) - u}{\sigma}\right]^4 = \frac{E\,[d_r(k) - u]^4}{\sigma^4} \quad (8)$$

$$E_r = \sum_{k=1}^{N} |d_r(k)|^2 \quad (9)$$

式中：$d_r(k)$—提升小波包终节点 r 第 k 个系数；N—系数的个数；j—小波包分解层数。

因考虑到能量数值往往较大，为便于后续分析与处理，故对能量进行归一化处理。这里 $E = (\sum_{r=1}^{2^j} |E_r|^2)^{1/2}$。

2　相关向量机

2.1　相关向量机算法

相关向量机（Relevance Vector Machine，RVM）是由 Tipping 提出的一种稀疏概率学习模型[9]，它克服了 SVM 惩罚函数的主观设置以及 SVM 核函数必须满足 Mercer 条件等问题。

给定训练样本集$\{(x_i, t_i)\}_{i=1}^{N}$，$x_i \in R^n$ 为输入向量，$y_i \in \{-1, 1\}$ 表示两个待分类的模式。RVM 的模型输出定义为：

$$f(x, w) = \sum_{i=1}^{N} w_i K(x, x_i) + w_0 \quad (10)$$

式中：w_i—模型权值，$K(x, x_i)$—核函数。本研究采用 RBF 高斯核函数：

$$K(x, x_i) = \exp\left[-\frac{\| x - x_i \|^2}{2\sigma^2}\right] \quad (11)$$

式中：σ—核函数的宽度。

假设噪声 ε_i 服从均值为零，方差为 σ^2 的高斯分布，则：

$$d_i = f(x_i, w) + \varepsilon_i \quad (12)$$

设 d_i 服从独立分布，则整个样本的似然函数为：

$$p(d_i | a, \sigma^2) = (2\pi\sigma^2)^{n/2} \exp\left[-\frac{1}{2\sigma^2} \| d - \theta \|^2\right] \quad (13)$$

式中：$\theta = \varphi_w$，$d = (d_1, d_2, \cdots, d_n)^T$。

RVM 为每一个权值定义了高斯先验概率分布：

$$p(w | a) = \prod_{i=1}^{n} n(w_i | 0, a_i^{-1}) \quad (14)$$

式中：a—超参数，它决定了模型的稀疏性，$w = (w_1, w_2, \cdots, w_n)$。

对于非线性分类器，存在一个从向量 x 到高维空间 H 的非线性映射函数 $\varphi(x)$ 使得 $K(x, x_i) = \varphi(x)\varphi(x_i)$。RVM 分类器可写成：

$$f(x) = \Phi^T(x)\,[\sum_{i=1}^{n} a_i \Phi(x_i)] \quad (15)$$

式中：$\Phi(x) = [\phi(x_1), \phi(x_2), \cdots, \phi(x_n)]^T$；$\phi(x_i) = [1, k(x_i, x_1), \cdots, k(x_i, x_n)]^T$。

2.2 基于二叉树的 RVM 多类分类器

为了适应离心泵多类分类情况，设计一种合理的多类分类器是获得高识别率的关键。最常用的组合方法中基于二叉树的方法具有更好的分类性能[11]。但二叉树的结构对整个分类模型的分类精度有较大影响，并且这种影响有可能产生“误差累积”现象，因此在二叉树的构造过程中，要合理选择二叉树的层次结构。目前主要有根据类距离法和类样本分布范围法两种途径构造二叉树[10]，而当出现两种类距离相等或分布范围相同的情况时，二叉树的构建就会受到影响。因此，文献[11]提出了一种综合考虑类距离与类分布范围两种因素的二叉树构建方法，具体流程如下：

(1) 在特征空间计算各类 S_i 与其它类的距离，此时可以把其它类归为一大类，按式(16)计算 $D\_S_i = D(S_i, S_r)$，按式(18)计算 r_i，计算 D_S_i/r_i，记为 $D_R\_S_i$，则：

$$D(S_p, S_q) = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}\delta(x_p^i, x_q^j) \tag{16}$$

$$\delta(x_p^i, x_q^j) = (x_p^i - x_q^j)^T (x_p^i - x_q^j) \tag{17}$$

$$r = \max_i\{\ \| \bar{x} - x_i \|\ \} \tag{18}$$

式中：x_p^i、x_q^j—类 S_p、S_q 中的第 i 个和第 j 个样本；样本数分别为 m 和 n 个。

(2) 对 $\{D_R\_S_i, (i = 1, \cdots, k)\}$ 按降序排序，不失一般性，设为 $\{S_1, \cdots, S_k\}$；

(3) 根据(2)中得到的顺序，依次训练得到相应的二类 RVM 分类器，可得到全部 $k-1$ 个二类 RVM，F：$\{RVM_1, \cdots, RVM_{k-1}\}$。

(4) 按 F 从二叉树根节点开始顺次构造内节点，即可构成多类分类器。

3 诊断实例分析

3.1 实验系统

实验系统中离心泵的型号为 2BA－6A，最大转速为 3 000 r/min，扬程为 25.2 m，流量为 20 m^3/h，效率为 65.6%，吸上真空高度为 7.2 m，离心泵为开式系统；电机的型号为 JZS2－51－1，主电压为 380 V，转速为 470～2 900 r/min，频率为 50 Hz。离心泵泵轴的垂直和水平方向用支架分别安装非接触式电涡流位移传感器测取径向位移；泵的联轴器其垂直面作为实验测试面，水平安装非接触电涡流位移传感器测取轴向位移。系统分别测取泵的正常状态、质量不平衡、转子不对中和基础松动振动位移信号。试验过程中转子转速由 500 r/min 上升到 2 900 r/min，每增加 20 r/min 采样一次，采用 INV306F 数据采集器进行采集，采样频率为 800 Hz，采样点数为 4096。实验系统如图 3 所示，系统照片如图 4 所示。

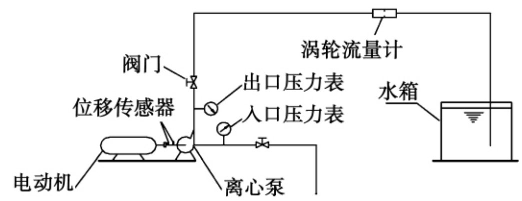

图 3　离心泵实验装置

Fig. 3 Test device for centrifugal pumps

图 4　试验装置照片

Fig. 4 Photo of the test device

质量不平衡的模拟是通过在联轴器位置安装 1 个圆盘，圆盘上装配重的螺钉来实现；不对中的模拟是通过将联轴器松开，使其偏离中心位置再紧固来实现；基础松动则是通过将电机底座固定螺栓松开一定程度来实现。正常、不对中、不平衡和松动 4 种状态的振动位移信号(径向位移传感器的输出信号)时域波形和频谱图如图 5～图 6 所示。

3.2 诊断过程

具体诊断步骤为：

(1) 测取离心泵不同状态下的数据。通过实验分别采集了 4 种状态下的振动数据(正常 30 组、不对中 38 组、不平衡 27 组和基础松动 31 组)共 126 组数据，每种状态各随机抽取 15 组用于样本训练，其余用于测试。

(2) 对各振动信号进行递归定量分析，提取提升小波包偏度系数、峭度系数和能量作为离心泵各状态的特征向量，表 1 给出了 4 种状态的部分特征向量。

(3) 输入训练样本特征向量，训练 RVM 二叉树分类器。

(4) 输入测试样本特征向量，测试 RVM 分器性

能。

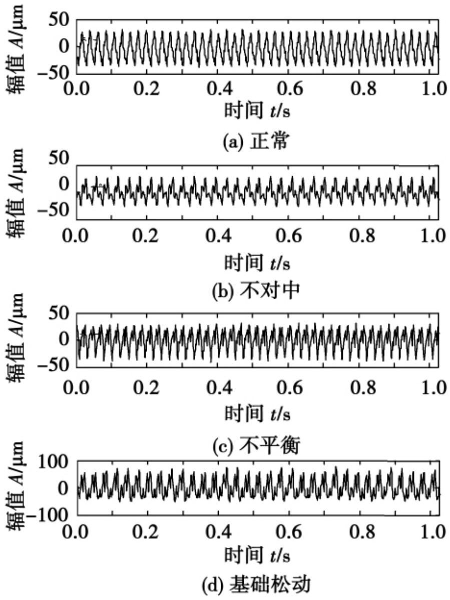

图 5　4 种状态下的时域波形

Fig. 5 Time-domain wave form in four states

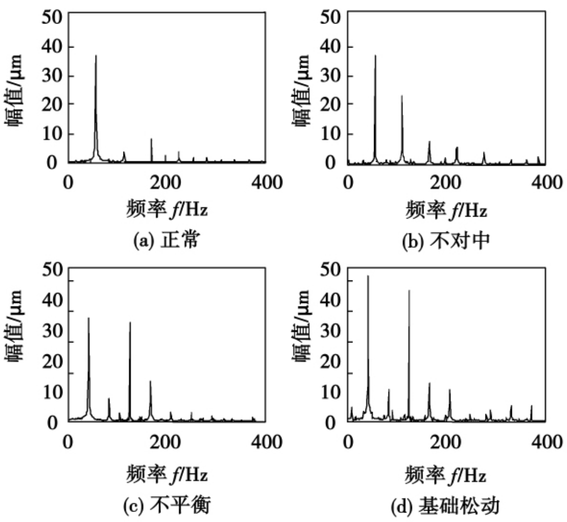

图 6　4 种状态振动信号的频谱图

Fig. 6 Spectrum of the vibration signal in four states

3.3　结果分析

SVM 是近几年公认的性能较好的分类器，这里主要在准确率(Classification Accuracy，AC) 、稀疏性和诊断时间(Diagnosis Time，DT) 3 方面将 RVM 与 SVM 进行对比。表 2 给出了对比结果，两种算法都采用高斯核函数作为基函数，表 2 中 SVs 代表支持向量(Support Vectors) ，RVs 代表相关向量(Relevance Vectors) 。

表 1　部分特征向量

Tab. 1 Partial chracteristic vector

状态	故障特征向量 T'
正常	0.82830.50230.05000.23460.02940.01320.0331 0.0208
正常	0.82890.50120.05260.23760.02810.01360.0339 0.0212
正常	0.83720.48920.05290.23360.02810.01330.0327 0.0213
正常	0.81600.52070.06030.23800.03060.01290.0343 0.0209
不对中	0.84280.39770.01680.36200.00060.00670.0096 0.0084
不对中	0.84550.38330.01530.37120.00080.00680.0086 0.0078
不对中	0.85270.36540.02090.37240.00080.00360.0074 0.0092
不对中	0.86080.36980.02370.34870.00050.00650.0077 0.0082
不平衡	0.96470.23100.03440.11880.00260.01270.0158 0.0183
不平衡	0.96100.25250.03330.10430.00280.01320.0159 0.0190
不平衡	0.96120.24420.03540.12020.00310.01310.0154 0.0192
不平衡	0.96290.24430.03500.10540.00360.01300.0163 0.0189
松动	0.83170.50050.01130.23920.00590.00790.0133 0.0098
松动	0.86380.41580.00820.28370.00500.00730.0125 0.0094
松动	0.84370.47180.00820.25550.00570.00750.0095 0.0135
松动	0.82990.49520.01160.25590.00640.00780.0114 0.0121

表 2　RVM 与 SVM 的对比

Tab. 2 Comparison of RVM and SVM

状态	RVM			SVM		
	AC/%	RVs	DT/s	AC/%	SVs	DT/s
正常	100	8	0.022	100	36	0.185
不对中	95.7	6	0.024	91.3	40	0.212
不平衡	91.7	7	0.027	83.3	32	0.196
松动	93.8	10	0.032	87.5	38	0.236

从表 2 中可以看出，除正常状态外，对其它 3 种故障状态的诊断率，RVM 都比 SVM 高，而且相关向量的数量比支持向量少很多。由于 RVM 引入了稀疏贝叶斯框架，稀疏性决定了诊断时间。正常状态下，RVM 的诊断时间为 0.022 s，综合看，RVM 的诊断时间约为 SVM 的 12.7%，说明 RVM 更适合在线诊断。

为了比较不同 RVM 多类分类算法的分类性能，将基于二叉树的 RVM 分类算法与“OAO”(One Against One) 方法、“OAR”(One Against Rest) 方法、“DAG”(Directed Acyclic Graph) 方法以及基于类距离二叉树方法“CDBT”(Binary Tree Based on Class Distance) 进行了对比，结果如表 3 所示，可以看出所研究方法诊断率最高。

由于“OAO”方法和“OAR”方法都存在不可分

区域,所以诊断率最低;“DAG”方法虽克服了上两种存在不可分区域的缺点,诊断率略有提高,但诊断效果受节点位置安排的限制,诊断率低于 CDBT 的诊断率。

表 3　几种分类方法的比较

Tab. 3 Comparison of classification methods

	训练时间/s	测试时间 /s	总诊断率 /%
OAR	4.232	0.024	89.4
OAO	4.436	0.026	90.9
DAG	4.187	0.032	92.4
CDBT	2.034	0.030	93.9
所研究的计算法	2.143	0.022	95.5

“OAO”和“DAG”方法在训练阶段构造分类器较多,需要 6 个,因此训练时间相对较长;在测试阶段“DAG”方法需要构造 3 个分类器,而“OAO”方法需要 6 个分类器,因此“DAG”方法比“OAO”方法测试时间短。“OAR”虽然需要 3 个分类器,但每个分类器的构建都需要用到所有样本,因此无论训练时间还是测试时间都较长。基于二叉树的 RVM 训练时只需构建 3 个分类器,并且随着诊断出的目标增多训练样本递减,因此训练和测试时间都短。本方法与基于类距离的二叉树方法相比,在训练和测试时间上相差不大,但因在构建二叉树时兼顾了类距离和类分布两种因素的影响,减少了累积误差的影响,具有最高的诊断率,达到了 95.5%。

4　结　论

根据离心泵振动信号的特点,提出了利用提升小波包和相关向量机的离心泵振动故障诊断方法。实验数据和分析结果表明:

(1) 提升小波包变换能快速把离心泵振动信号按频带划分,各频带信号的能量、偏度系数和峭度系数可有效反映离心泵不同状态的特征;

(2) 考虑类距离和类分布的二叉树相关向量机具有更高的诊断率,达到了 95.5%,稀疏性好于 SVM。与其他相关向量机分类算法相比,诊断时间短,只有 0.022 s,更适合在线诊断。

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lished. In most cases, the deviation between the value predicted by using the above-mentioned formula and the actually measured one is within in a range of ±10%, indicating that the formula can be used for on-line operation control and prediction of NO_x emissions concentration of a boiler. **Key words**: supercritical boiler, wall-type combustion system, low NO_x emission, operating factor, multi-variable linear regression

AVT 水工况条件下水冷壁管形成氧化膜的特性研究 = **Study of the Formation Characteristics of Oxide Film on Waterwall Tubes Under the AVT(All Volatilization Treatment) Water Condition** [刊,汉] ZHANG Hui, ZHU Zhi-ping, XING Ling-ling, et al(College of Chemical and Biological Engineering, Changsha University of Science and Technology, Changsha, China, Post Code: 410114) //Journal of Engineering for Thermal Energy & Power. – 2011, 26(6). –732 ~737

By using electrochemical, XRD, SEM/EDAX etc. testing methods, studied were the morphology and structure of the oxide film on the waterwall tubes of a 600 MW boiler formed in the process of oxidation after 18 hours at 300 ℃ under both AVT (all-volatile treatment) (R) and AVT (O) water condition with the mechanism for forming such oxide film being analyzed. The research findings can offer guidance for reducing the high temperature corrosion of metals in actual operations. It has been found that the oxide film formed under the AVT (R) condition can be divided into two layers. The inner layer represents an inner extension layer of Fe_3O_4, which grows inwards by contacting with the metal body and the outer layer represents a uniform and compact layer, being in black color and wholly overlaid on the metal surface. However, the oxide film formed under the AVT(O) water condition can be divided into three layers, i. e. an inner layer of the oxide film (inner extension layer of Fe_3O_4), an intermediate compact layer of Fe_3O_4, which covers the whole surface layer of the specimen and on which oxide Fe_2O_3 also grows as large crystal particles, thus, an outer layer is formed. **Key words**: AVT (all-volatile treatment) (R) /(O), waterwall tube, oxide film, film formation mechanism

基于提升小波包的离心泵故障诊断方法 = **Method for Diagnozing the Fault of a Centrifugal Pump Based on a Lifting Wavelet Package** [刊,汉] ZHOU Yun-long, SUN Bin (College of Energy Source and Power Engineering, Northeast Electric Power University, Jilin, China, Post Code: 132012), ZHAO Peng (College of Energy Source and Power Engineering, North China University of Electric Power, Beijing, China, Post Code: 102206) // Journal of Engineering for Thermal Energy & Power. – 2011, 26(6). –738 ~742

To accurately diagnose the vibration fault of a centrifugal pump, presented was a method for diagnosing the vibration fault of a centrifugal pump based on a lifting wavelet package and a relevant vector mahine. Firstly, the lifting wavelet method was used to quickly extract the decomposition coefficient energy and time-domain statistical parameters of vibration signals in various states to serve as the characteristic variables. In the light of the problem of a low speed in diagnosis due to a low sparsity of the supporting vector machine, a relevant vector machine can be utilized to accomplish the classification diagnosis. The research results show that the method in question can effectively diagnose any vibration fault of a centrifugal pump with its diagnostic rate being as high as 95.5%. Compared with other algorithms, the method under discussion takes a short time for testing and needs only 0.022 seconds, thus more suitable for on-line diagnosis. **Key words**: centrifugal pump, fault diagnosis, lifting wavelet package, relevant vector machine

Einstein 循环制冷机导流式气泡泵的性能研究 = **Study of the Performance of a Flow Guided Bubble Pump Destined for Einstein Cycle Refrigerators** ［刊，汉］ PING Ya-qin, LIU Dao-ping, CHEN Sheng-xiang, et al(Refrigeration Technology Research Institute, Shanghai University of Science and Technology, Shanghai, China, Post Code: 200093) // Journal of Engineering for Thermal Energy & Power. – 2011, 26(6). –743 ~ 746

In the light of such demerits of a bubble pump as low in efficiency and incapable of effectively utilizing low quality unsteady heat source etc., presented was a flow guided bubble pump with its lifting performance being experimentally studied. Under a given operation condition, the influence of various heating powers and immersion ratios on the liquid lifting quantity was also investigated. The test curves were given and compared with those of the traditional bubble pumps. The test results show that when the diameter of the lifting tube is 16 mm and the immersion ratio is 0.4, the startup power of the flow guided bubble pump can decrease by 100 W and the lifting efficiency can increase by 13%, proving that flow guided bubble pumps are characterized by such remarkable features as a low startup power, high efficiency and energy-saving etc. The analytic results are of major significance for enhancing the efficiency of a bubble pump and the performance of an Einstein cycle refrigerator. **Key words**: flow guided bubble pump, low quality heat source, liquid lifting quantity

粒子群优化算法及其在发电机组调速系统参数辨识中的应用 = **Particle Colony Algorithm and Its Application in Discriminating Parameters of a Speed Regulation System of a Generator Unit** ［刊，汉］ LI Yang-hai, WANG Kun, HUANG Shu-hong, et al(College of Energy Source and Power Engineering, Central China University of Science and Technology, Wuhan, China, Post Code: 430074) // Journal of Engineering for Thermal Energy & Power. – 2011, 26(6). –747 ~ 750

Accurate and reliable model parameters of a speed regulation system of a generator unit are most important for analyzing the stability of its electric power system. As the requirements for test conditions are relatively rigorous when the conventional discrimination methods (such as least square method) are used to discriminate the parameters of a model, so it is very difficult to identify the parameters existing in a large quantity of a nonlinear link of a speed regulation system. The authors introduced a particle colony algorithm, which is now the hot research point, into the identification process of model parameters of the speed regulation system of a power generator unit. The research results show that when using the particle colony theory to discriminate model parameters, it can achieve a quick calculation speed and an accurate and reliable discrimination result and solve very well the intractable technical problems in identifying parameters of a nonlinear link of a speed regulation system. In the meantime, the algorithm enjoys a good universality and through a user definition of the model, it can be used for discriminating the parameters of a grey box model, **Key words**: generator unit, speed regulation system, parameter discrimination, Matlab, par-