

模糊超体神经网络 及其在火箭发动机故障分离中的应用

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【摘要】提出了一种用模糊集表示火箭发动机故障模式的神经网络二次分离器,模糊集是由模糊超体聚集形成的集合体,模糊超体在一次分离中表现为由半径和球心确定的 n 维超球,在二次分离中是一个由夹角、球心和方向矢量确定的部分超球。神经网络二次分离学习算法与一次学习算法相比,提高了训练样本的分离精度,增强了神经网络对故障的敏感性。仿真研究表明模糊超体神经网络可以成功地应用于泵压式液体火箭发动机故障检测与分离。

主题词: 液体推进剂火箭发动机 故障诊断 神经网络

分类号: O 235 V 430

1 故障模糊分离

神经网络通过自学习能提取同类发动机故障的模式特征,因此采用模式识别方法,神经网络可以有效完成发动机的故障检测与分离^[1]。

用于发动机故障检测与分离的三层模糊超体神经网络如图1所示,输入层有 n 个信息处理单元。超体层自适应形成,超体隶属函数 b_j 用来度量输入向量 $A_h^T = (a_1, a_2, \dots, a_n)$ 与球心 $O_j^T = (o_{j1}, o_{j2}, \dots, o_{jn})$ 、夹角 φ_j 和方向矢量 $W_j^T = (w_{j1}, w_{j2}, \dots, w_{jn})$ 确定的超体之间的相似性,在此超体节点的隶属函数定为:

$$b_j = \min \{ 1 - \max [0, \min [\varphi_1, \varphi_2]] \}$$
$$1 - \max [0, \min [\varphi_1, \varphi_2]]$$

$$\varphi_1 = \arccos \frac{(A_h - O_j) \cdot W_j}{(\|A_h - O_j\| \times \|W_j\|)}$$

$$\varphi_2 = 2^{\text{sym}} \varphi_{10}, \quad \varphi_1 = 2^{\text{sym}} \varphi_{20} \quad (1)$$

式中,符号 $\| \cdot \|$ 表示向量的绝对值,sym是超体的标识量,灵敏参数 φ_1, φ_2 反映输入向量在远离超体时,它们之间在切向和径向的隶属度降低速率。若超体的夹角扩大到 2π ,超体变为超球,超球的半径等于超体方向矢量的模,隶属函数也相应变为

$$b_j = 1 - \max \left\{ 0, \min [\varphi_1, \varphi_2] \right\} \quad (2)$$

神经网络的输出层一故障类层有 p 个处理单元,超体层与故障类层联结权值是二值矢量

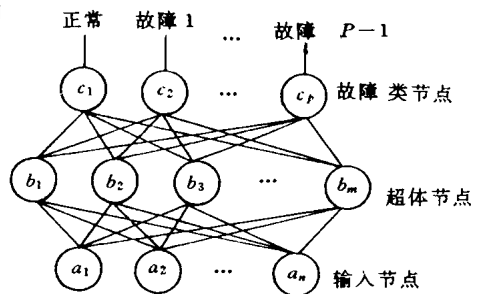


图1 模糊超体神经网络分离器

$\{0, 1\}^p$, 计算公式为

$$u_{jk} = \begin{cases} 1 & b_j \in c_k \\ 0 & \text{others} \end{cases}$$

式中, c_k 是故障类层的第 k 个节点输出值。故障类层节点的传递函数是同一类超体模糊集的并集, 即定义为 $c_k = \max_{j=1}^m b_j u_{jk}$

2 二次分离学习算法

2.1 模糊超球学习算法

模糊超球学习是一个超球扩张与收缩过程, 训练集 D 由一系列样本对 $\{A_h, d_h\}$ 构成, 其中 $A_h = (a_{h1}, a_{h2}, \dots, a_{hn})$ 是输入向量, $d_h \in \{1, 2, \dots, p\}$ 是故障模式的索引。

超球扩张: 已知某一样本对 $\{A_h, d_h\} \in D$, 找到最近似的超球 B_{j_0} 。若要超球 B_j 扩张到包 A_h , 必须满足条件限制 $\|A_h - O_j\| < \theta$, $\|A_h - O_j\| > V_{j_0}$ 式中 θ 是选定常数, 用来限制超球大小。若两条件满足, 则超球 B_j 的球心和半径调整公式为

$$r_j^{\text{new}} = (1/2) (\|A_h - O_j^{\text{old}}\| + r_j^{\text{old}})$$

$$O_j^{\text{new}} = O_j^{\text{old}} + (r_j^{\text{new}} - r_j^{\text{old}}) (A_h - O_j^{\text{old}}) / \|A_h - O_j^{\text{old}}\|$$

超球重叠测试: 为了测试是否产生重叠, 须在两模糊超球之间进行比较。若下面 3 种条件之一得到满足, 两个超球之间必有重叠部分。假定 B_j 刚经过扩张, B_k 代表另一超球, 3 种测试条件描述如下, $|r_j - r_k| < \|O_j - O_k\| < r_j + r_k$; $\|O_j - O_k\| < r_j - r_k$; $\|O_j - O_k\| < r_k - r_{j_0}$

超球收缩: 如果超球 B_j 与超球 B_k 发生重叠, 并属于不同的故障类, 必须消除超球之间的重叠。利用超球重叠测试给出的 3 种测试条件, 得到相应的超球收缩算法为

$$1: \quad r_j^{\text{new}} = \frac{1}{2} (r_j^{\text{old}} - r_k^{\text{old}} + \|O_j^{\text{old}} - O_k^{\text{old}}\|), \quad r_k^{\text{new}} = \frac{1}{2} (r_k^{\text{old}} - r_j^{\text{old}} + \|O_j^{\text{old}} - O_k^{\text{old}}\|)$$

$$O_j^{\text{new}} = O_j^{\text{old}} + (r_j^{\text{old}} - r_j^{\text{new}}) \frac{O_j^{\text{old}} - O_k^{\text{old}}}{\|O_j^{\text{old}} - O_k^{\text{old}}\|}, \quad O_k^{\text{new}} = O_k^{\text{old}} + (r_k^{\text{old}} - r_k^{\text{new}}) \frac{O_k^{\text{old}} - O_j^{\text{old}}}{\|O_k^{\text{old}} - O_j^{\text{old}}\|}$$

$$2: \quad r_j^{\text{new}} = (1/2) (r_j^{\text{old}} - r_k^{\text{old}} + \|O_j^{\text{old}} - O_k^{\text{old}}\|)$$

$$O_j^{\text{new}} = O_k^{\text{old}} + \frac{r_j^{\text{old}} + r_k^{\text{old}} + \|O_j^{\text{old}} - O_k^{\text{old}}\|}{2 \|O_j^{\text{old}} - O_k^{\text{old}}\|} (O_j^{\text{old}} - O_k^{\text{old}}), \quad \text{if } \|O_j^{\text{old}} - O_k^{\text{old}}\| \neq 0$$

$$O_j^{\text{new}} = (\|O_j^{\text{old}}\| + r_j^{\text{new}} + r_k^{\text{old}}) O_j^{\text{old}} / \|O_j^{\text{old}}\|, \quad \text{if } \|O_j^{\text{old}} - O_k^{\text{old}}\| = 0$$

$$3: \quad r_j^{\text{new}} = (1/2) (r_k^{\text{old}} - r_j^{\text{old}} + \|O_j^{\text{old}} - O_k^{\text{old}}\|)$$

$$O_k^{\text{new}} = O_j^{\text{old}} + \frac{r_k^{\text{old}} + r_j^{\text{old}} + \|O_j^{\text{old}} - O_k^{\text{old}}\|}{2 \|O_j^{\text{old}} - O_k^{\text{old}}\|} (O_j^{\text{old}} - O_k^{\text{old}}), \quad \text{if } \|O_j^{\text{old}} - O_k^{\text{old}}\| \neq 0$$

$$O_j^{\text{new}} = (\|O_k^{\text{old}}\| + r_k^{\text{new}} + r_j^{\text{old}}) O_k^{\text{old}} / \|O_k^{\text{old}}\|, \quad \text{if } \|O_j^{\text{old}} - O_k^{\text{old}}\| = 0$$

2.2 输入样本标识

模糊神经网络经过一次分离学习, 得到了每类发动机故障的非线性模式边界。由于训练样本空间之间一般有重叠, 因此样本空间在经过超球分割之后, 有一些点划分在故障模式类之外, 甚至划分为其它故障模式类, 即表现为故障的漏分离及误分离。为了进一步对训练样本进行二次分离, 必须首先对一次分离结果进行标识, 具体实现为: (1) 若 $\|A_h - O_j\| < r_j$ 且 $u_{jd_h} = 1$, 则输入样本的标识量 $\text{symbol} = 0$ 。(2) 若 $\|A_h - O_j\| > r_j$ 且 $u_{jd_h} = 0$, 则输入样本的标识量

symbol= 2。(3)若不能找到超球满足以上两条件,则输入样本的标识量 symbol= 1。

2 3 模糊超体学习算法

模糊神经网络二次分离学习在一次分离基础上对训练样本再次精炼。样本标识量为 0 代表输入样本属于其故障模式类,只需在超球内进一步分离;1 表示输入样本漏分离,需要在超球外进行再分离;2 表示样本误分离,需去掉这样的训练样本或让其形成一些弧点。

超球内超体扩张:若 $\|A_h - O_j'\| \leq r_j'$ 且输入样本的标识量 symbol= 0,则输入样本属于超球 j' 。当在超球内建立一个新超体时,设置超体的标识量为 0。若夹角满足条件 $v_j^{old}/2 < \varphi < \theta$ (θ 用于限制超体夹角大小),则超体的夹角扩张为 $v_j^{new} = \varphi - v_j^{old}/2, \varphi - (\varphi - v_j^{old}/2)/2$ 。

若有 $\|A_h - O_j\| \leq \|W_j\|$,超体 j 的方向矢量更新公式为

$$W_j^{new} = W_j^{old} + \|W_j^{old}\| \operatorname{tg}(\varphi) \frac{\left(\frac{\|W_j^{old}\|}{\cos(v_j^{new}/2)} \times \frac{A_h - O_j}{\|A_h - O_j\|} - W_j^{old} \right)}{\left\| \frac{\|W_j^{old}\|}{\cos(v_j^{new}/2)} \times \frac{A_h - O_j}{\|A_h - O_j\|} - W_j^{old} \right\|}$$

若有 $\|A_h - O_j\| > \|W_j\|$,超体 j 的方向矢量更新公式为

$$W_j^{new} = \frac{\|A_h - O_j\|}{\cos(\varphi)} \times \frac{W_j^{old}}{\|W_j^{old}\|} + \frac{\frac{A_h - O_j}{\cos(v_j^{new}/2)} - \frac{\|A_h - O_j\|}{\cos(\varphi)} \times \frac{W_j^{old}}{\|W_j^{old}\|}}{\left\| \frac{A_h - O_j}{\cos(v_j^{new}/2)} - \frac{\|A_h - O_j\|}{\cos(\varphi)} \times \frac{W_j^{old}}{\|W_j^{old}\|} \right\|} \times \|A_h - O_j\| \times \operatorname{tg}(\varphi)$$

超球外超体扩张:若 $\|A_h - O_j'\| > r_j'(j = 1, 2, \cdots, m)$ 且输入样本的标识量 symbol= 1,则输入样本属于超球外一点,在一次分离学习中,它不属于任何一类,在二次分离学习中,必须形成新的超体来代表这些样本。超球外超体扩张算法与超球内超体扩张算法一样,若超体扩张后不与其它类超体重叠,接收此次超体扩张,否则建立一个新超体,并设置 $O_j = A_h, v_j = 0, W_j = 0$,超体标识量 sym= 1。若 $\|A_h - O_j'\| > r_j'$ 且输入样本的标识量 symbol= 2,则输入样本误分离为其它类,建立一个弧点来表示输入样本,即 $O_j = A_h, v_j = 0, W_j = 0$,超体标识量 sym= 2。

3 发动机故障分离的仿真研究

模糊超体神经网络的训练样本选取见表 1,共有 250 个训练样本,选自发动机故障的随机

表 1 模糊超体神经网络的训练样本

发动机工作模式	数据代号	故障程度	样本数
正 常	OUT		40
氧化剂主活门未完全打开	OUTD7、D8、D9	打开 55、50、45 度	10
燃料主活门未完全打开	OUTF6、F7、F8	打开 45、40、35 度	10
两主活门都未完全打开	OUTE4、E5、E6	打开 55、50、45 度	10
氧化剂泵汽蚀	OUTG		20
燃料泵汽蚀	OUTH		20
两泵同时汽蚀	OUTI		20
副系统氧化剂过滤网阻塞	OUTJ7、J9、J11	阻力系数 60、80、100 倍	10
副系统燃料管路泄漏	OUTK4、K5、K6	泄漏比为 0.4、0.5、0.6	100

模拟,泄漏比定义为泄漏流量与副系统燃料流量之比。模糊超体神经网络的输入结点数为 7,

输出节点为 9, 灵敏参数 $\gamma_{10}=3, \gamma_{20}=4$, 阈值 $\theta_1=0.06, \theta_2=1.0$ 。在一次分离学习中, 共形成 27 个超球, 在二次分离学习中, 共形成 157 个超体, 其中, 标识量为 0 的超体 95 个, 标识量为 1 的超体 46 个, 标识量为 2 的超体 16 个。

模糊超体神经网络学习好以后, 用不同于训练故障程度的发动机随机模拟数据进行测试,

表 2 发动机随机模拟故障的分离结果

数据 代号	发动机实际 工作模式	故障程度	一次分离结果		二次分离结果	
			类型	敏感度	类型	敏感度
OUT1	正 常		0	1.251	0	1.629
OUTDA11	氧化剂主活门未全打开	打开 51.5 度	1, 3	1.168	1	1.481
OUTDA14	氧化剂主活门未全打开	打开 47 度	1, 3	1.167	1	1.878
OUTFA7	燃料主活门未全打开	打开 41.5 度	2	1.243	2	2.433
OUTFA10	燃料主活门未全打开	打开 34 度	2	1.429	2	5.604
OUTEA5	两主活门都未全打开	打开 53.5 度	3, 1	1.189	3	1.343
OUTEA10	两主活门都未全打开	打开 43 度	3, 1	1.187	3	1.538
OUTG	氧化剂泵汽蚀		4	1.353	4	1.785
OUTH	燃料泵汽蚀		5	3.935	5	5.570
OUTI	两泵同时汽蚀		6	1.696	6	3.098
OUTJ8	副系统氧化剂过滤网阻塞	70 倍阻力系数	8, 7	1.180	7, 8	1.354
OUTJ10	副系统氧化剂过滤网阻塞	90 倍阻力系数	8, 7	1.145	7, 8	1.310
OUTKA9	副系统燃料管路泄漏	泄漏比为 0.525	8, 7	1.181	8, 7	1.383
OUTKA10	副系统燃料管路泄漏	泄漏比为 0.55	8, 7	1.166	7, 8	1.382

测试结果见表 2, 分离结果中的类型号 0, 1, $\cdots$, 8 分别代表发动机的 9 种工作模式, 敏感度指同一时刻神经网络的最大与次最大输出值之比在整个测试时间内的平均值。对于发动机正常模式、燃料主活门未全打开模式和 3 种汽蚀故障模式, 模糊超体神经网络一次故障分离和二次故障分离结果都非常正确, 但二次分离结果的敏感度比一次分离结果大。对于氧化剂主活门未全打开模式和两主活门都未打开模式, 一次分离结果有误, 但二次分离结果正确。由于副系统氧化剂过滤网阻塞模式与副系统燃料管路泄漏模式非常近似, 基于选择的 7 个性能参数, 二次分离学习算法也很难区分它们, 即发动机故障分离出现二义性问题, 但若进一步采用解析冗余方法求得副系统组元比, 两种副系统故障将能正确分离。

结论 用模糊集表示液体火箭发动的故障模式, 可以容易地形成故障模式的非线性边界, 在学习过程中可以不断融合新的故障特征和精练已存在的发动机故障模式。模糊超体神经网络的二次学习算法分离发动机故障比一次学习算法更加敏感, 分离故障的精度更高。

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Key Words Afterburners Airfilm cooling Heat transfer

NUMERICAL CALCULATION OF FLOW FIELD INSIDE A SMALL ENGINE ANNULAR REVERSE- FLOW COMBUSTOR

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ABSTRACT Calculations of flow field with fuel injection and heat release inside an annular reverse- flow combustor of a small aeroengine have been performed with a 3- D elliptic turbulent reacting thermo- aerodynamic software. In the program the turbulence is simulated by the k- ϵ two- equations model, the combustion after vaporization is determined by a two- step chemical reaction model, the reaction rate is calculated with Arrhenius and eddy breakup model. The SIMPLE algorithm is used to solve the finite- difference equations. The complex boundary conditions are treated particularly. Predictions of gas temperature, velocity, and fuel/air ratio show that a strong vortex emerges in the primary zone of liner; the velocity circumferential distributions have a similarity; the combustor performance is satisfactory due to favourable matching between velocity and fuel/air ratio distributions. The small circumferential velocities contribute to a reasonable velocity distribution at turbine start.

Key Words Combustion chambers Flow fields Numerical simulation

NUMERICAL SIMULATION OF HOT FLOW IN LIQUID ROCKET ENGINE COMBUSTOR WITH AND WITHOUT BAFFLE

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ABSTRACT The hot flow fields in liquid rocket engine combustion chamber with and without baffles are simulated numerically. The gas governing equations are described by Navier- Stokes equations in the Euler coordinates. The liquid governing equations are represented in the Lagrangian coordinates. The droplet moving tracks in the hot solutions of the two cases are investigated. The flow field parameters of the combustion chamber are compared between the two hot solutions. It is proved that the numerical treatment of the baffle is valid.

Key Words Combustion chambers Liquid propellant rockets Numerical simulation

FUZZY HYPER- BODY NEURAL NETWORK AND ITS APPLICATION TO ROCKET ENGINE FAULT ISOLATION

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ABSTRACT A neural network twice classifier is provided which utilizes fuzzy sets as fault patterns of a liquid propellant rocket engine. Each fuzzy set is an aggregate of fuzzy hyperbodies. A fuzzy hyper- body is an n- dimensional hyper- sphere defined by a radius and a center with a corresponding membership function at first learning of fuzzy neural network and a part of the hyper- sphere defined by an included angle, a center and a direction vector at second learning. The training isolation accuracy of the twice learning algorithm

is higher than that of the once learning algorithm, and the twice learning of fuzzy neural network also enhances sensitivity to rocket fault. The twice learning algorithm can learn nonlinear fault pattern boundaries in two passes through the input data and provides the ability to incorporate new fault messages in succession and refine existing fault classes without retraining. The emulation of its application indicates that the fuzzy hyper-body neural network can be successfully employed in the fault detection and isolation of the turbo-pump feed liquid rocket engine.

Key Words Liquid rocket engines Fault diagnosis Neural networks

TECHNICAL NOTES

CREEP RELIABILITY CALCULATION OF TURBINE DISK WITH ODM

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ABSTRACT Integration Order Descending Method (ODM) is a new approximate method for solving the mathematical problems in the reliability. There are some difficulties to solve the engineering problems with the ODM. This paper shows how to use ODM for this purpose and applies it to calculating the creep reliability of an aeroengine turbine disc. This paper also presents the loads that have been considered in calculation of the turbine disc creep with ADZNA program.

Key Words Turbines Discs Creep Reliability

ANALYSIS OF POTENTIAL ENERGY OF COMPLEX ROTOR-CASE SYSTEM BY USING WHOLE TRANSFER MATRIX METHOD

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ABSTRACT An improved transfer matrix method - Whole Transfer Matrix method was applied to calculation of the critical speeds and vibration modes of a dual-rotor system with engine casing. Its potential energy distributions corresponding to each rotor critical speed and vibration mode are calculated and analyzed by this way. Whole Transfer Matrix method takes rotors and cases of the system as a whole body in transferring, the size of the frequency determinant is determined only by the number of rotors and cases, but free from the supports. This method is of great advantage for developing general computer program. The investigation indicated that the vibration level of the rotor system can be found from potential energy distribution. Thus the effective measures can be taken to depress the vibration.

Key Words Transfer functions Strain energy Vibration effects