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可变学习增益的迭代学习控制律

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摘要: 基于迭代学习控制理论提出了一种可变学习增益的迭代学习律, 在非线性系统中对期望轨迹进行跟踪, 与学习增益不变的迭代学习控制相比较, 收敛速度得到很大的提高; 通过对其收敛性进行严格的数学证明, 得到了迭代学习律收敛的充分条件; 在单机无穷大系统中, 将该控制律应用于同步发电机的励磁控制, 仿真结果表明该控制律的有效性, 改善了控制的动态特性, 有利于提高电力系统稳定性.

关键词: 迭代学习控制; 单机–无穷大系统; 收敛性; 同步发电机; 励磁控制

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Iterative learning control law with variable learning gain

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Abstract: An iterative learning law with variable gain is proposed based on iterative learning control theory. The convergence is strictly proved mathematically and sufficient conditions are obtained. The control law is then applied to the excitation control of synchronous machines in single machine to infinite system. Simulations are also performed by MATLAB/SIMULINK in the single machine to infinite system to demonstrate the validity and universality of the method.

Key words: iterative learning control; a single machine to infinite system; convergence; synchronous machine; excitation control

1 引言(Introduction)

迭代学习控制利用系统先前的控制经验和输出误差来修正当前的控制信息, 以简单的学习算法, 在给定的时间区间上实现未知被控对象以任意精度跟踪给定的期望轨迹[1]. 控制器在运行过程中不需要辨识系统的参数, 属于基于品质的自学习控制, 非常适用于解决各种非线性控制问题, 且需要较少的先验知识. 文献[2]中线性迭代学习控制的控制增益都为常数不可调, 虽然其控制性能与PID控制器相比有一定改善, 但收敛速度还是比较慢, 如果控制初始值任意设置, 必须迭代多次才能使跟踪误差小到允许范围, 因而本文提出了一种可变学习增益的迭代学习控制律, 它的增益系数为$e, \dot{e}, \int e$的函数, 在非线性系统中对期望轨迹进行跟踪, 只需迭代两次就能使跟踪误差接近于零, 收敛速度与学习增益不变的迭代学习控制相比较, 得到很大的提高. 采用的系统未作线性化处理, 因而本文实现的是对非线性系统的精确控制.

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2 收敛性分析(Convergence analyze)

对于如图1所示单机–无穷大系统的动态方程具有式(1)所示的标准仿射型非线性系统的形式.

完全满足Lipschitz条件.

$$\begin{cases} \dot{x}(t) = f(t, x(t)) + g(t)u(t), \\ y(t) = h(t, x(t)). \end{cases} \tag{1}$$

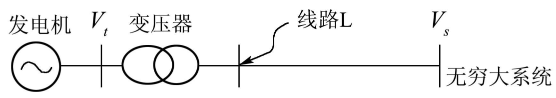


图 1 单机–无穷大系统

Fig. 1 Single machine to infinite system

电力系统的功率振荡频率变化不大, 如果把功角的每一次摇摆看作一个控制周期, 那么, 电力系统机电暂态的稳定控制便可看作是周期性的控制, 因此可用迭代学习控制方法实现同步发电机的励磁控制. 采用式(2)所示的学习律:

$$u_{k+1}(t) = u_k(t) + [(k_{11}e_k(t) + k_{12}\dot{e}_k(t) + k_{13}\int_0^t e_k(s)\mathrm{d}s)e_k(t) + (k_{21}e_k(t) + k_{22}\dot{e}_k(t) + k_{23}\int_0^t e_k(s)\mathrm{d}s)\dot{e}_k(t) + (k_{31}e_k(t) + k_{32}\dot{e}_k(t) + k_{33}\int_0^t e_k(s)\mathrm{d}s)\int_0^t e_k(s)\mathrm{d}s]. \quad (2)$$

输出方程中不含直接传输项, 存在$M_1, M_2, M_3 > 0$且满足:

A1)

$$\|f(t,x_1) - f(t,x_2)\| \leqslant M_1\|x_1 - x_2\|, \forall x_1, x_2 \in \mathbb{R}^n,$$
$$\|h(t,x_1) - h(t,x_2)\| \leqslant M_2\|x_1 - x_2\|, \forall x_1, x_2 \in \mathbb{R}^n,$$
$$\|\dot{h}(t,x_1) - \dot{h}(t,x_2)\| \leqslant M_3\|x_1 - x_2\|, \forall x_1, x_2 \in \mathbb{R}^n,$$

A2) 每次运行时的初始状态误差$\{\delta x_k(0)\}_{k\geqslant 0}$为一收敛到零的序列;

A3) 存在惟一的理想控制$u_d(t)$, 使得系统的状态和输出为期望值;

A4) 在$t \in [0,T]$中$\dot{h}(t,x(t))$存在, 且$g(t)$, $h(t,x(t))$有界.

定义

$$\begin{cases} \delta x_k(t) = x_d(t) - x_k(t), \\ \delta y_k(t) = y_d(t) - y_k(t), \\ \delta u_k(t) = u_d(t) - u_k(t), \end{cases} \quad (3)$$

其中: $y_d(t), x_d(t), u_d(t)$为期望轨迹上的输出、状态和控制. $y_k(t), x_k(t), u_k(t)$为第k次迭代的输出、状态和控制.

学习控制收敛性问题在于研究学习律满足什么条件下, 当学习次数$k \to \infty$时, $y_k(t), x_k(t), u_k(t)$是否趋于$y_d(t), x_d(t), u_d(t)$, 该问题等价于当$k \to \infty$时$\delta y_k(t), \delta x_k(t), \delta u_k(t)$是否趋于零.

由式(1)~(3)得:

$$\begin{cases} \delta x_k(t) = f_1(t,\delta x_k(t)) + g(t)\delta u_k(t), \\ \delta u_{k+1}(t) = \delta u_k(t) - [k_{11}\delta y_k(t)^2 + k_{22}\delta\dot{y}_k(t)^2 + k_{33}\int_0^t \delta y_k(s)^2\mathrm{d}s + (k_{12}+k_{21})\delta y_k(t)\delta\dot{y}_k(t) + (k_{31}+k_{13})\delta y_k(t)\int_0^t \delta y_k(s)\mathrm{d}s + (k_{32}+k_{23})\delta y_k(t)\int_0^t \delta y_k(s)\mathrm{d}s]. \end{cases} \quad (4)$$

令

$$f_1(t,\delta x_k(t)) = f(t,\delta x_d(t)) - f(t,\delta x_k(t)),$$
$$h_1(t,\delta x_k(t)) = h(t,\delta x_d(t)) - h(t,\delta x_k(t)),$$

且有

$$\delta\dot{y}_k(t) = \dot{h}_{1t}(t,\delta x_k(t)) + \dot{h}_{1x}(t,\delta x_k(t))\dot{x}_d(t) + \dot{h}_{1x}(t,x_k(t))\delta\dot{x}_k(t), \quad (5)$$

$$\int_0^t \delta y_k(s)\mathrm{d}s = \int_0^t h_1(s,\delta x_k(s))\mathrm{d}s, \quad (6)$$

$$\delta u_{k+1}(t) = \delta u_k(t) - [k_{11}h_1^2(t,\delta x_k(t)) + k_{22}[\dot{h}_{1t}(t,\delta x_k(t)) + \dot{h}_{1x}(t,\delta x_k(t))\dot{x}_d(t) + \dot{h}_x(t,x_k(t))\delta\dot{x}_k(t)]^2 + k_{33}(\int_0^t h_1(s,\delta x_k(s))\mathrm{d}s)^2 + (k_{31}+k_{13})h_1(t,\delta x_k(t))\int_0^t h_1(s,\delta x_k(s))\mathrm{d}s + (k_{32}+k_{23})[\dot{h}_{1t}(t,\delta x_k(t)) + \dot{h}_{1x}(t,\delta x_k(t))\dot{x}_d(t) + \dot{h}_x(t,x_k(t))\delta\dot{x}_d(t)]\int_0^t h_1(s,\delta x_k(s))\mathrm{d}s,$$

整理得

$$\delta u_{k+1}(t) = \{[1 - 2k_{22}\dot{h}_{1t}(t,\delta x_k(t))g(t)\dot{h}_x(t,x_k(t)) - 2k_{22}\dot{h}_{1t}(t,\delta x_k(t))g(t)\dot{h}_x(t,x_k(t)) - 2k_{22}f_1(t,\delta x_k(t))g(t)\dot{h}_x(t,x_k(t))^2 + (k_{12}+k_{21})h_1(t,\delta x_k(t))\dot{h}_x(t,x_k(t))g(t) + (k_{32}+k_{23})h_x(t,x_k(t))\int_0^t h_1(s,x_k(s))\mathrm{d}sg(t)] - k_{22}\dot{h}_x(t,x_k(t))^2 g(t)^2\delta u_k(t)\}\delta u_k(t) - \{k_{11}\dot{h}_1(t,\delta x_k(t))^2 + k_{22}\dot{h}_{1t}(t,\delta x_k(t))^2 + 2k_{22}\dot{h}_{1t}(t,\delta x_k(t))\dot{h}_{1x}(t,\delta x_k(t))\dot{x}_d(t) + k_{22}\dot{h}_{1x}(t,\delta x_k(t))^2\dot{x}_d(t)^2 + 2k_{22}\dot{h}_{1t}(t,\delta x_k(t))f_1(t,\delta x_k(t))\dot{h}_x(t,x_k(t)) + 2k_{22}\dot{h}_{1x}(t,\delta x_k(t))\dot{x}_d(t)f_1(t,\delta x_k(t))\dot{h}_x(t,x_k(t)) + k_{22}f_1(t,\delta x_k(t))^2\dot{h}_x(t,x_k(t))^2 + k_{33}\int_0^t h_1(s,\delta x_k(s))^2\mathrm{d}s + (k_{12}+k_{21})h_1(t,\delta x_k(t))\dot{h}_{1t}(t,\delta x_k(t)) + (k_{12}+k_{21})h_1(t,\delta x_k(t))\dot{h}_{1x}(t,\delta x_k(t))\dot{x}_d(t) + (k_{12}+k_{21})h_1(t,\delta x_k(t))\dot{h}_x(t,x_k(t))f_1(t,\delta x_k(t)) + (k_{31}+k_{13})h_1(t,\delta x_k(t))\int_0^t h_1(s,\delta x_k(s))\mathrm{d}s + (k_{32}+k_{23})\dot{h}_{1t}(t,\delta x_k(t))\int_0^t h_1(s,\delta x_k(s))\mathrm{d}s + (k_{32}+k_{23})\dot{h}_{1x}(t,\delta x_k(t))\dot{x}_d(t)\int_0^t h_1(s,\delta x_k(s))\mathrm{d}s + (k_{32}+k_{23})\dot{h}_x(t,x_k(t))\int_0^t h_1(s,\delta x_k(s))\mathrm{d}s\, f_1(t,\delta x_k(t))\}. \quad (7)$$

定义算子$P: C_r[0,T] \to C_r[0,T]$

$$(P\delta u)(t) = \{[1-2k_{22}\dot{h}_{1t}(t,\delta x_k(t))g(t)\dot{h}_x(t,x_k(t)) - 2k_{22}\dot{h}_{1t}(t,\delta x_k(t))g(t)\dot{h}_x(t,x_k(t)) - 2k_{22}f_1(t,\delta x_k(t))g(t)\dot{h}_x(t,x_k(t))^2 + (k_{12}+k_{21})h_1(t,\delta x_k(t))\dot{h}_x(t,x_k(t))g(t) + (k_{32}+k_{23})h_x(t,x_k(t))\int_0^t h_1(s,x_k(s))\mathrm{d}sg(t)] - k_{22}\dot{h}_x(t,x_k(t))^2 g(t)^2\delta u_k(t)\}\delta u_k(t)\}. \tag{8}$$

定义算子$Q: C_r[0,T]\to C_r[0,T]$

$$Q_k(\delta u)(t) = -\{k_{11}\dot{h}_1(t,\delta x_k(t))^2 + k_{22}\dot{h}_{1t}(t,\delta x_k(t))^2 + 2k_{22}\dot{h}_{1t}(t,\delta x_k(t))\dot{h}_{1x}(t,\delta x_k(t))\dot{x}_d(t) + k_{22}\dot{h}_{1x}(t,\delta x_k(t))^2\dot{x}_d(t)^2 + 2k_{22}\dot{h}_{1t}(t,\delta x_k(t))f_1(t,\delta x_k(t))\dot{h}_x(t,x_k(t)) + 2k_{22}\dot{h}_{1x}(t,\delta x_k(t))\dot{x}_d(t)f_1(t,\delta x_k(t))\dot{h}_x(t,x_k(t)) + k_{22}f_1(t,\delta x_k(t))^2\dot{h}_x(t,x_k(t))^2 + k_{33}\int_0^t h_1(s,\delta x_k(s))^2\mathrm{d}s + (k_{12}+k_{21})h_1(t,\delta x_k(t))\dot{h}_{1t}(t,\delta x_k(t)) + (k_{12}+k_{21})h_1(t,\delta x_k(t))\dot{h}_{1x}(t,\delta x_k(t))\dot{x}_d(t) + (k_{12}+k_{21})h_1(t,\delta x_k(t))\dot{h}_x(t,x_k(t))f_1(t,\delta x_k(t)) + (k_{31}+k_{13})h_1(t,\delta x_k(t))\int_0^t h_1(s,\delta x_k(s))\mathrm{d}s + (k_{32}+k_{23})\dot{h}_{1t}(t,\delta x_k(t))\int_0^t h_1(s,\delta x_k(s))\mathrm{d}s + (k_{32}+k_{23})\dot{h}_{1x}(t,\delta x_k(t))\dot{x}_d(t)\int_0^t h_1(s,\delta x_k(s))\mathrm{d}s + (k_{32}+k_{23})\dot{h}_x(t,x_k(t))\int_0^t h_1(s,\delta x_k(s))\mathrm{d}sf_1(t,\delta x_k(t))\}. \tag{9}$$

由式(4)(8)(9)可知

$$\delta u(t) = (P+Q_k)(P+Q_{k-1})\cdots(P+Q_0)(\delta u_0)(t). \tag{10}$$

根据条件A1) A4), 存在$M_4, M_8, M_{12}>0$,

$$\begin{cases}\|f_1(t,\delta x_k(t)\|\leqslant M_1\|\delta x_k(t)\|,\\ \|\delta y_k(t)\| = \|h_1(t,x(t))\|\leqslant M_4\|\delta x_k(t)\|,\\ \|\int_0^t\delta y_k(s)\mathrm{d}s\| = \|\int\delta y_1(s)\mathrm{d}s\|\leqslant M_{12}\|\delta x_k(t)\|,\\ \|\dot{h}_1(t,\delta x_k(t)\|\leqslant M_8\|\delta x_k(t)\|.\end{cases} \tag{11}$$

以下对Q_k作出估计:

$$Q_k\leqslant \|k_{11}\dot{h}_1(t,\delta x_k(t))^2\| + \|k_{22}\dot{h}_{1t}(t,\delta x_k(t))^2\| + \|2k_{22}\dot{h}_{1t}(t,\delta x_k(t))\dot{h}_{1x}(t,\delta x_k(t))\dot{x}_d(t)\| + \|k_{22}\dot{h}_{1x}(t,\delta x_k(t))^2\dot{x}_d(t)^2\| + 2\|k_{22}\dot{h}_{1t}(t,\delta x_k(t))f_1(t,\delta x_k(t))\dot{h}_x(t,x_k(t))\| + 2\|k_{22}\dot{h}_{1x}(t,\delta x_k(t))\dot{x}_d(t)f_1(t,\delta x_k(t))\cdot \dot{h}_x(t,x_k(t))\| + \|k_{22}f_1(t,\delta x_k(t))^2\dot{h}_x(t,x_k(t))^2\| + \|k_{33}\int_0^t h_1(s,\delta x_k(s))^2\mathrm{d}s\| + \|(k_{12}+k_{21})h_1(t,\delta x_k(t))\dot{h}_{1t}(t,\delta x_k(t))\| + \|(k_{12}+k_{21})h_1(t,\delta x_k(t))\dot{h}_{1x}(t,\delta x_k(t))\dot{x}_d(t)\| + \|(k_{12}+k_{21})h_1(t,\delta x_k(t))\dot{h}_x(t,x_k(t))f_1(t,\delta x_k(t))\| + \|(k_{31}+k_{13})h_1(t,\delta x_k(t))\int_0^t h_1(s,\delta x_k(s))\mathrm{d}s\| + \|(k_{32}+k_{23})\dot{h}_{1t}(t,\delta x_k(t))\int_0^t h_1(s,\delta x_k(s))\mathrm{d}s\| + \|(k_{32}+k_{23})\dot{h}_{1x}(t,\delta x_k(t))\int_0^t h_1(s,\delta x_k(s))\mathrm{d}s\| + \|(k_{32}+k_{23})\dot{h}_x(t,x_k(t))\int_0^t h_1(s,\delta x_k(s))\mathrm{d}s\, f_1(t,\delta x_k(t))\| + \leqslant\delta x(t). \tag{12}$$

如果$x(t)$是动态方程(1)的解, 则

$$\|x(t)\| = \|x(0)+\int_0^t[f(s,x(s))+g(s)u(s)]\mathrm{d}s\|.$$

由条件A1)可得

$$\|x(t)\|\leqslant\|x(0)\|+\int_0^t\|x(s)\|\mathrm{d}s+\int_0^t\|g(s)u(s)\|\mathrm{d}s.$$

由Bellman-Gronwell引理知, 存在$M_6>0$使得

$$\|x(t)\|\leqslant M_6(\|x(0)\|+\int_0^t\|u(s)\|\mathrm{d}s). \tag{13}$$

由式(9)(13)知, 存在$M_7>0$使得

$$\|Q_k(u)(t)\|\leqslant M_7(\|x(0)\|+\int_0^t\|u(s)\|\mathrm{d}s),$$

同理

$$\|Q_k(\delta u)(t)\|\leqslant M_7(\|\delta x(0)\|+\int_0^t\delta u(s)\mathrm{d}s). \tag{14}$$

根据式(10) (14)及条件A2)和附录中的定理得到算法收敛的充分条件是:

$$2|k_{22}|M_1M_8\max_{t\in[0,T]}|x_d(t)| - M > 0, \tag{15}$$

其中:

$$M = 2|k_{22}|M_8 + 2|k_{22}|\max_{t\in[0,T]}|\dot{x}_d(t)|M_8 + 2|k_{22}|M_8M_1\max_{t\in[0,T]}|x_d(t)| + |k_{12}+k_{21}|M_8 + |k_{32}+k_{23}|M_{12},$$

将式(11)代入并整理简化可得

$$|k_{11}|M_3{}^2+|k_{22}|M_8{}^2+2|k_{22}|M_8{}^2\max_{t\in[0,T]}|\dot{x}_d(t)|+ |k_{22}|M_8{}^2\max_{t\in[0,T]}|\dot{x}_d(t)^2|+ 2|k_{22}|M_8M_1\max_{t\in[0,T]}|\dot{h}_x(t,x(t))|+ 2|k_{22}|M_8M_1\max_{t\in[0,T]}|\dot{h}_x(t,x(t))|\max_{t\in[0,T]}|\dot{x}_d(t)|+ |k_{22}|M_1{}^2\max_{t\in[0,T]}|\dot{h}_x(t,x(t))^2|+|k_{33}|M_{12}{}^2+ |k_{12}+k_{21}|M_8M_3+|k_{12}+k_{21}|M_8M_3\max_{t\in[0,T]}|\dot{x}_d(t)|+ |k_{12}+k_{21}|M_3M_1\max_{t\in[0,T]}|\dot{h}_x(t,x(t))|+ |k_{31}+k_{13}|M_3M_{12}+|k_{32}+k_{23}|M_8M_{12}+ |k_{32}+k_{23}|M_8M_{12}\max_{t\in[0,T]}|\dot{x}_d(t)|\max_{t\in[0,T]}|x_d(t)|+ \max_{t\in[0,T]}|x(t)|<1, \tag{16}$$

也就是式(15) (16)同时成立时, 式(2)所示控制律收敛. 可见, 如果状态方程满足如A1)∼A4)所示的Lipschitz条件, 则收敛条件与状态方程的结构形式无关.

3 仿真研究(Simulation)

同步发电机的状态方程采用转子四绕组的模型共6阶(转子绕组4阶, 运动方程两阶)[4]. 假定发电机与电力系统处于同步运行状态, 考虑线路阻抗中电阻的比重很小, 只计及电抗[5]. 如图1所示的单机–无穷大系统, 采用PSB工具箱进行仿真研究, 控制律如式(4)所示, 与式(17)(18)所示的迭代学习控制律和常规PID进行仿真比较.

$$u_{k+1}(t)=u_k(t)+\Gamma_pe_k(t)+\Gamma_d\dot{e}_k(t)+\Gamma_i\int_0^t e_k(s)\mathrm{d}s, \tag{17}$$

$$u(t)=k_pe(t)+k_d\dot{e}(t)+k_i\int_0^t e(s)\mathrm{d}s. \tag{18}$$

在式(2)所示的控制律中, 根据式(15)和(18)结合具体被控系统的各参数可以计算各控制增益参数, 实际上收敛条件反映的是一个收敛范围, 取其同时满足式(15)(16)的公共数值范围, 计算过程类似于文献[2], 此处限于篇幅, 仅将计算结果表示如下:

$$k_{11}=10, k_{12}=1.2, k_{13}=1.6,$$
$$k_{21}=0.008, k_{22}=0.0004, k_{23}=0.004,$$
$$k_{31}=0.03, k_{32}=0.03, k_{33}=0.03,$$

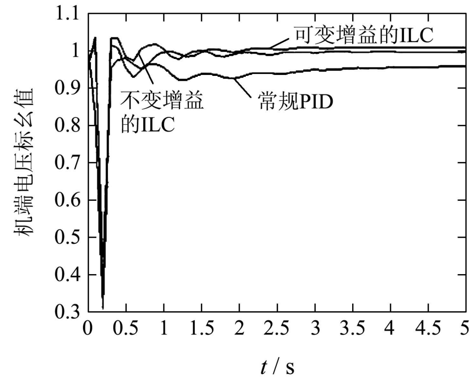
式(17)控制律的各控制增益参数为: $\Gamma_p=2, \Gamma_d=0.3, \Gamma_i=0.3$, 式(18)控制律的各控制增益参数为:

$$k_p=15, k_d=0.3, k_i=0.3.$$

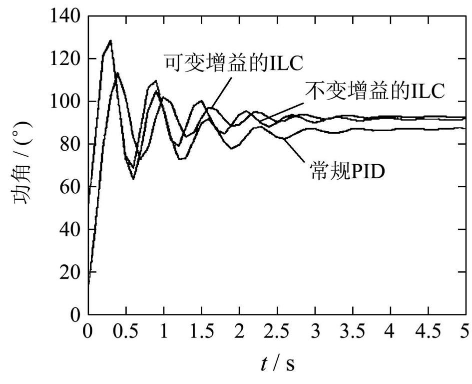
如图1所示单机–无穷大系统, 额定容量为200 MVA, 额定电压13.8 kV的三相同步发电机通过210 MVA, △–Y接线的变压器与母线电压为230 kV的无穷大系统相连, 系统参数如下(标幺值):

$$\omega_0=1\ \text{p.u.}, D=5.0\ \text{p.u.}, H=4.0\ \text{s},$$
$$T_{d0}=6.9, x'_{d\Sigma}=1.02665\ \text{p.u.},$$
$$x_{d\Sigma}=2.23265\ \text{p.u.}, x'_d=1\ \text{p.u.}, x'_q=1\ \text{p.u.},$$
$$x_d=1.863\ \text{p.u.}, \delta_0=15^\circ, P_{m0}=8.0\ \text{p.u.}.$$

$t=0.1$ s时, 在变压器的230 kV侧母线上发生三相对地短路, $t=0.2$ s时故障切除, 仿真波形如图2所示.



(a) 同步发电机的机端电压



(b) 同步发电机的功角

图 2 3种控制方式下的仿真波形

Fig. 2 Simulation waves of three controllers

常规PID型, 不变增益的迭代学习和可变增益的迭代学习3种控制方式下的仿真波形如图2所示, 由仿真波形可知, 采用可变增益的迭代学习控制方式只需迭代2次就可以收敛, 并在1 s左右就把机端电压恢复到允许范围内, 不变增益的迭代学习控制需要迭代8次才能达到与前者一样的控制效果, 而常规PID控制的各增益系数一旦确定, 特性就很难改善, 不像其他两种控制可以通过迭代逐步改善. 与其他两种控制方式相比, 可变增益的迭代学习控制方

式的性能最佳, 但此时的稳定裕度有所减小.

4 结论(Conclusion)

可变增益的迭代学习控制律在满足一定的条件下可以收敛, 从仿真结果可知, 单机–无穷大系统中发生三相故障时, 该控制律具有很强的维持机端电压的能力, 且收敛速度大大加快, 可变增益系数的增加使其易于改善控制的动态性能. 可见, 增益系数可变的非线性迭代学习控制算法具有广阔的应用前景, 值得深入探讨. 迭代学习控制理论在同步发电机励磁控制中的应用还处于初步阶段, 许多问题还有待进一步的深入研究.

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