

1 代码

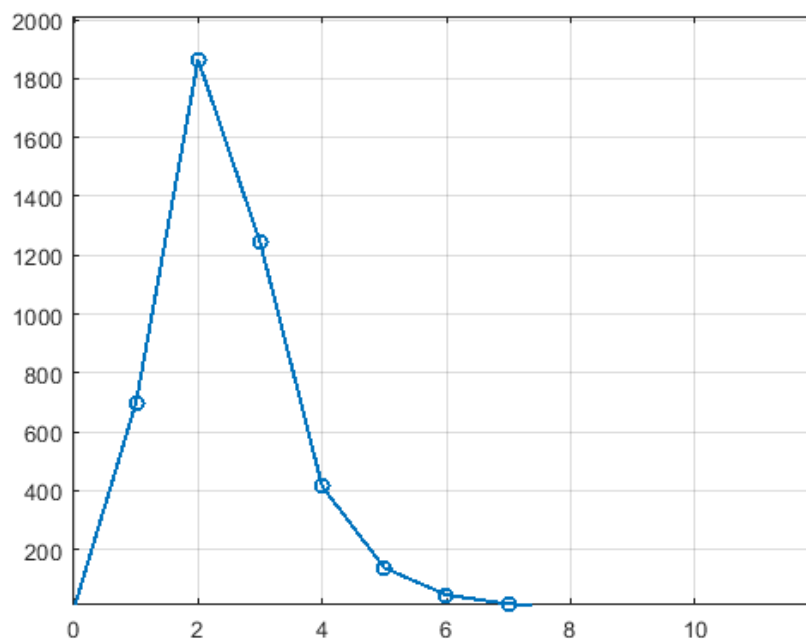
1.1 阻尼因子变化曲线图

首先编译文件得到数值

```
monster@monster-Luo:/media/monster/学习资料/网课/手写VIO/course3_CurveFitting_LM/build$ cd ..
monster@monster-Luo:/media/monster/学习资料/网课/手写VIO/course3_CurveFitting_LM$ ./build/app/testCurveFitting

Test CurveFitting start...
iter: 0 , chi= 36048.3 , Lambda= 0.001
iter: 1 , chi= 30015.5 , Lambda= 699.051
iter: 2 , chi= 13421.2 , Lambda= 1864.14
iter: 3 , chi= 7273.96 , Lambda= 1242.76
iter: 4 , chi= 269.255 , Lambda= 414.252
iter: 5 , chi= 105.473 , Lambda= 138.084
iter: 6 , chi= 100.845 , Lambda= 46.028
iter: 7 , chi= 95.9439 , Lambda= 15.3427
iter: 8 , chi= 92.3017 , Lambda= 5.11423
iter: 9 , chi= 91.442 , Lambda= 1.70474
iter: 10 , chi= 91.3963 , Lambda= 0.568247
iter: 11 , chi= 91.3959 , Lambda= 0.378832
problem solve cost: 4.31742 ms
makeHessian cost: 2.77042 ms
-----After optimization, we got these parameters :
0.941939 2.09453 0.965586
-----ground truth:
1.0, 2.0, 1.0
monster@monster-Luo:/media/monster/学习资料/网课/手写VIO/course3_CurveFitting_LM$
```

lambda 值整理后，在 matlab 下绘图



1.2 完成曲线 $y = ax^2 + bx + c$ 的参数估计

需要将代码中的 $y = \exp(ax^2 + bx + c)$ 改为 $y = ax^2 + bx + c$ ，以及修改残差和对应雅可比

```
residual_(0) = abc(0)*x_*x_ + abc(1)*x_ + abc(2) - y_; // 构建残差
jaco_abc << x_ * x_ , x_ , 1 ;//雅可比
```

重新编译运行

```
终端
monster@monster-Luo: /media/monster/学习资料/网课/手写VIO/course3_CurveFitting_LM/build/app
文件(F) 编辑(E) 查看(V) 搜索(S) 终端(T) 帮助(H)
monster@monster-Luo: /media/monster/学习资料/网课/手写VIO/course3_CurveFitting_LM/build/app$ ./testCurveFitting

Test CurveFitting start...
iter: 0 , chi= 719.475 , Lambda= 0.001
iter: 1 , chi= 91.395 , Lambda= 0.000333333
problem solve cost: 0.756702 ms
makeHessian cost: 0.5008 ms
-----After optimization, we got these parameters :
1.61039 1.61853 0.995178
-----ground truth:
1.0, 2.0, 1.0
monster@monster-Luo: /media/monster/学习资料/网课/手写VIO/course3_CurveFitting_LM/build/app$
```

参数估计误差较大，误差较大的原因可能是数据点数量不足。于是将数据点由 100 增加到 1200,再次编译，得到参数估计精度就足够高了

```
monster@monster-Luo: /media/monster/学习资料/网课/手写VIO/course3_CurveFitting_LM/...
文件(F) 编辑(E) 查看(V) 搜索(S) 终端(T) 帮助(H)
monster@monster-Luo: /media/monster/学习资料/网课/手写VIO/course3_CurveFitting_LM
pp$ ./testCurveFitting

Test CurveFitting start...
iter: 0 , chi= 7.40976e+06 , Lambda= 49.6628
iter: 1 , chi= 1198.81 , Lambda= 16.5543
iter: 2 , chi= 1195.27 , Lambda= 5.51809
iter: 3 , chi= 1195.26 , Lambda= 2.06615
problem solve cost: 13.0162 ms
makeHessian cost: 10.3522 ms
-----After optimization, we got these parameters :
0.999637 2.00403 0.974341
-----ground truth:
monster@monster-Luo: /media/monster/学习资料/网课/手写VIO/course3_CurveFitting_LM
pp$
```

1.3 实现其他更优秀的阻尼因子策略

...

2. 关于 F 和 G 的公式推导

2.1
1) $f_{15} = \frac{\partial a_{b_1 b_{k+1}}}{\partial s b_k^g}$

$a = \frac{1}{2} (q_{b_1 b_k} (a^{b_k} - b_k^g) + q_{b_1 b_k} \otimes [\frac{1}{2} w s t] (a^{b_{k+1}} - b_k^g))$

$w = \frac{1}{2} ((w^{b_k} + n_k^g - b_k^g) + (w^{b_{k+1}} + n_{k+1}^g - b_k^g)) = \frac{1}{2} ((w^{b_k} + n_k^g) + (w^{b_{k+1}} + n_{k+1}^g)) - b_k^g$

$a_{b_1 b_{k+1}} = a_{b_1 b_k} + \beta_{b_1 b_k} + \frac{1}{2} a s t^2$

b_k^g 与 w 相关, 误差传递, 对 w 在 $s b_k^g s t$ 求偏导:

$f_{15} = \frac{\partial a_{b_1 b_{k+1}}}{\partial s b_k^g} = \frac{\partial \frac{1}{2} a s t^2}{\partial s b_k^g}$

$= \frac{\partial \frac{1}{2} q_{b_1 b_k} \otimes [\frac{1}{2} w s t] (a^{b_{k+1}} - b_k^g) s t^2}{\partial s b_k^g}$

$\Rightarrow \frac{1}{4} \frac{\partial q_{b_1 b_k} \otimes [\frac{1}{2} w s t] \otimes [\frac{1}{2} s b_k^g s t] (a^{b_{k+1}} - b_k^g) s t^2}{\partial s b_k^g}$

$= \frac{1}{4} \frac{\partial R_{b_1 b_{k+1}} \exp(-\frac{1}{2} s b_k^g s t) (a^{b_{k+1}} - b_k^g) s t^2}{\partial s b_k^g}$

$= \frac{1}{4} \frac{\partial R_{b_1 b_{k+1}} (I + [-\frac{1}{2} s b_k^g s t]_x) (a^{b_{k+1}} - b_k^g) s t^2}{\partial s b_k^g}$

$= -\frac{1}{4} \frac{\partial R_{b_1 b_{k+1}} [(a^{b_{k+1}} - b_k^g)_x s t^2 (-s b_k^g s t)]}{\partial s b_k^g}$

$= -\frac{1}{4} (R_{b_1 b_{k+1}} [(a^{b_{k+1}} - b_k^g)_x s t^2] (-s t))$

2) $g_{12} = \frac{\partial a_{b_1 b_{k+1}}}{\partial s n_k^g}$

$a = \frac{1}{2} (q_{b_1 b_k} (a^{b_k} - b_k^g) + q_{b_1 b_k} \otimes [\frac{1}{2} w s t] (a^{b_{k+1}} - b_k^g))$

$w = \frac{1}{2} ((w^{b_k} + n_k^g - b_k^g) + (w^{b_{k+1}} + n_{k+1}^g - b_k^g)) = \frac{1}{2} ((w^{b_k} + n_k^g) + (w^{b_{k+1}} + n_{k+1}^g)) - b_k^g$

$a_{b_1 b_{k+1}} = a_{b_1 b_k} + \beta_{b_1 b_k} + \frac{1}{2} a s t^2$

对 w 在 $s n_k^g s t$ 求偏导:

$g_{12} = \frac{\partial a_{b_1 b_{k+1}}}{\partial s n_k^g} = \frac{\partial \frac{1}{2} a s t^2}{\partial s n_k^g} = \frac{1}{4} \frac{\partial q_{b_1 b_k} \otimes [\frac{1}{2} w s t] (a^{b_{k+1}} - b_k^g) s t^2}{\partial s n_k^g}$

$\Rightarrow \frac{1}{4} \frac{\partial q_{b_1 b_k} \otimes [\frac{1}{2} w s t] \otimes [-\frac{1}{2} s n_k^g s t] (a^{b_{k+1}} - b_k^g) s t^2}{\partial s n_k^g}$

$= \frac{1}{4} \frac{\partial R_{b_1 b_{k+1}} \exp(-\frac{1}{2} s n_k^g s t) (a^{b_{k+1}} - b_k^g) s t^2}{\partial s n_k^g}$

$= \frac{1}{4} \frac{\partial R_{b_1 b_{k+1}} (I - [\frac{1}{2} s n_k^g s t]_x) (a^{b_{k+1}} - b_k^g) s t^2}{\partial s n_k^g}$

$= -\frac{1}{4} \frac{\partial R_{b_1 b_{k+1}} [(a^{b_{k+1}} - b_k^g)_x s t^2 (\frac{1}{2} s n_k^g s t)]}{\partial s n_k^g}$

$= -\frac{1}{4} (R_{b_1 b_{k+1}} [(a^{b_{k+1}} - b_k^g)_x s t^2] (\frac{1}{2} s t))$

3. 证明式(9)

题 3

根据矩阵运算推导:

$$\Delta X_{lm} = - \sum_{j=1}^n \frac{V_j^T F'^T}{\lambda_j + \mu} V_j,$$

$$(J^T J + \mu I) \Delta X_{lm} = -J^T f, \mu \geq 0$$

$J^T J$ 为半正定信息矩阵, 特征值 $\{\lambda_j\}$. 满足 $J^T J = V \Lambda V^T$, 其中 V 为 $J^T J$ 特征向量组成的特征矩阵, 向量之间相互正交.

Λ 为特征值组成的对角阵. $F'(x) = (J^T f)^T$

且因为 V 为正交阵, 具有性质 $V^T = V^{-1}$

$$(J^T J + \mu I) \Delta X_{lm} = -J^T f$$

$$\begin{aligned} \Delta X_{lm} &= (J^T J + \mu I)^{-1} (-J^T f) \\ &= (V \Lambda V^T + \mu V V^T)^{-1} (-J^T f) \\ &= (V \Lambda V^T + V \mu I V^T)^{-1} (-J^T f) = [V(\Lambda + \mu I)V^T]^{-1} (-F'^T) \end{aligned}$$

展开:

$$[V_1 \ V_2 \ \dots \ V_n] \begin{bmatrix} \frac{1}{\lambda_1 + \mu} & 0 & \dots & 0 \\ 0 & \frac{1}{\lambda_2 + \mu} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \frac{1}{\lambda_n + \mu} \end{bmatrix} \begin{bmatrix} V_1^T \\ V_2^T \\ \vdots \\ V_n^T \end{bmatrix} (-F'^T)$$

$$= \begin{bmatrix} \frac{V_1}{\lambda_1 + \mu} & \frac{V_2}{\lambda_2 + \mu} & \dots & \frac{V_n}{\lambda_n + \mu} \end{bmatrix} \begin{bmatrix} -V_1^T F'^T \\ -V_2^T F'^T \\ \vdots \\ -V_n^T F'^T \end{bmatrix} = - \sum_{j=1}^n \frac{V_j V_j^T F}{\lambda_j + \mu}$$