NLPImplicitSolver

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```
from casadi import *
from numpy import *
from pylab import *
```

We will investigate the working of rootfinder with the help of the parametrically exited Duffing equation.
Parameters

```
eps   = SX.sym("eps")
mu    = SX.sym("mu")
alpha = SX.sym("alpha")
k     = SX.sym("k")
sigma = SX.sym("sigma")
params = [eps,mu,alpha,k,sigma]
```

Variables

```
a     = SX.sym("a")
gamma = SX.sym("gamma")
```

Equations

```
res0 = mu*a+1.0/2*k*a*sin(gamma)
res1 = -sigma * a + 3.0/4*alpha*a**3+k*a*cos(gamma)
```

Numerical values

```
sigma_ = 0.1
alpha_ = 0.1
k_     = 0.2
params_ = [0.1,0.1,alpha_,k_,sigma_]
```

We create a NLPImplicitSolver instance

```
f=Function("f", [vertcat(a, gamma), vertcat(*params)], [vertcat(res0, res1)])
opts = {}
opts["nlpsol"] = "ipopt"
opts["nlpsol_options"] = {"ipopt.tol":1e-14}
s=rootfinder("s", "nlpsol", f, opts)

x_ = s([1,-1], params_)
```

```
******************************************************************************

This program contains Ipopt, a library for large-scale nonlinear
    optimization.
 Ipopt is released as open source code under the Eclipse Public License (
    EPL).
         For more information visit http://projects.coin-or.org/Ipopt
******************************************************************************
```

```
This is Ipopt version 3.12.3, running with linear solver ma57.

Number of nonzeros in equality constraint Jacobian...:        4
Number of nonzeros in inequality constraint Jacobian.:        0
Number of nonzeros in Lagrangian Hessian.............:        3

Total number of variables............................:        2
                     variables with only lower bounds:        0
                variables with lower and upper bounds:        0
                     variables with only upper bounds:        0
Total number of equality constraints.................:        2
Total number of inequality constraints...............:        0
        inequality constraints with only lower bounds:        0
   inequality constraints with lower and upper bounds:        0
        inequality constraints with only upper bounds:        0

iter    objective    inf_pr   inf_du lg(mu)  ||d||  lg(rg) alpha_du
    alpha_pr  ls
   0  0.0000000e+00 8.31e-02 0.00e+00  -1.0 0.00e+00    -  0.00e+00 0.00e
     +00   0
   1  0.0000000e+00 1.23e-02 0.00e+00  -2.5 2.40e-01    -  1.00e+00 1.00e
     +00h  1
   2  0.0000000e+00 2.02e-03 0.00e+00  -3.8 2.00e-01    -  1.00e+00 1.00e
     +00h  1
   3  0.0000000e+00 1.28e-03 0.00e+00  -3.8 1.15e-01    -  1.00e+00 1.00e
     +00h  1
   4  0.0000000e+00 4.42e-05 0.00e+00  -5.7 2.96e-02    -  1.00e+00 1.00e
     +00h  1
   5  0.0000000e+00 2.30e-05 0.00e+00  -5.7 1.68e-02    -  1.00e+00 1.00e
     +00h  1
   6  0.0000000e+00 5.32e-06 0.00e+00  -5.7 8.03e-03    -  1.00e+00 1.00e
     +00h  1
   7  0.0000000e+00 1.34e-06 0.00e+00  -8.6 3.98e-03    -  1.00e+00 1.00e
     +00h  1
   8  0.0000000e+00 3.35e-07 0.00e+00  -8.6 1.98e-03    -  1.00e+00 1.00e
     +00h  1
   9  0.0000000e+00 8.38e-08 0.00e+00  -8.6 9.87e-04    -  1.00e+00 1.00e
     +00h  1
iter    objective    inf_pr   inf_du lg(mu)  ||d||  lg(rg) alpha_du
    alpha_pr  ls
  10  0.0000000e+00 2.10e-08 0.00e+00  -8.6 4.93e-04    -  1.00e+00 1.00e
    +00h  1
  11  0.0000000e+00 5.24e-09 0.00e+00 -12.9 2.46e-04    -  1.00e+00 1.00e
    +00h  1
  12  0.0000000e+00 1.31e-09 0.00e+00 -12.9 1.23e-04    -  1.00e+00 1.00e
    +00h  1
  13  0.0000000e+00 3.28e-10 0.00e+00 -12.9 6.15e-05    -  1.00e+00 1.00e
    +00h  1
  14  0.0000000e+00 8.19e-11 0.00e+00 -12.9 3.08e-05    -  1.00e+00 1.00e
    +00h  1
  15  0.0000000e+00 2.05e-11 0.00e+00 -12.9 1.54e-05    -  1.00e+00 1.00e
    +00h  1
  16  0.0000000e+00 5.12e-12 0.00e+00 -12.9 7.69e-06    -  1.00e+00 1.00e
    +00h  1
  17  0.0000000e+00 1.28e-12 0.00e+00 -12.9 3.84e-06    -  1.00e+00 1.00e
    +00h  1
```

```
  18  0.0000000e+00 3.20e-13 0.00e+00 -12.9 1.92e-06    -  1.00e+00 1.00e
      +00h  1
  19  0.0000000e+00 8.00e-14 0.00e+00 -15.0 9.61e-07    -  1.00e+00 1.00e
      +00h  1
iter    objective    inf_pr   inf_du lg(mu)  ||d||  lg(rg) alpha_du
     alpha_pr  ls
  20  0.0000000e+00 2.00e-14 0.00e+00 -15.0 4.80e-07    -  1.00e+00 1.00e
      +00h  1
  21  0.0000000e+00 5.04e-15 0.00e+00 -15.0 2.40e-07    -  1.00e+00 1.00e
      +00h  1

Number of Iterations....: 21

                                   (scaled)                 (unscaled)
Objective...............:   0.0000000000000000e+00    0.0000000000000000e
    +00
Dual infeasibility......:   0.0000000000000000e+00    0.0000000000000000e
    +00
Constraint violation....:   5.0404780683255265e-15    5.0404780683255265e
    -15
Complementarity.........:   0.0000000000000000e+00    0.0000000000000000e
    +00
Overall NLP error.......:   5.0404780683255265e-15    5.0404780683255265e
    -15


Number of objective function evaluations             = 22
Number of objective gradient evaluations             = 22
Number of equality constraint evaluations            = 22
Number of inequality constraint evaluations          = 0
Number of equality constraint Jacobian evaluations   = 22
Number of inequality constraint Jacobian evaluations = 0
Number of Lagrangian Hessian evaluations             = 21
Total CPU secs in IPOPT (w/o function evaluations)   =      0.003
Total CPU secs in NLP function evaluations           =      0.001

EXIT: Optimal Solution Found.
                   proc           wall       num           mean
                                    mean
                   time           time       evals         proc time
                       wall time
       nlp_f      0.000 [s]      0.000 [s]     22         0.00 [ms]
           0.00 [ms]
       nlp_g      0.000 [s]      0.000 [s]     22         0.00 [ms]
           0.01 [ms]
  nlp_grad_f      0.000 [s]      0.000 [s]     23         0.00 [ms]
      0.00 [ms]
   nlp_jac_g      0.000 [s]      0.000 [s]     23         0.00 [ms]
       0.01 [ms]
  nlp_hess_l      0.000 [s]      0.000 [s]     21         0.00 [ms]
      0.02 [ms]
 all previous     0.000 [s]      0.001 [s]
callback_prep     0.000 [s]      0.000 [s]     22         0.00 [ms]
    0.01 [ms]
      solver      0.000 [s]      0.007 [s]
    mainloop      0.000 [s]      0.008 [s]
```

```python
print "Solution = ", x_
```

```
Solution =  [1.1547, -1.5708]
```

Compare with the analytic solution:

```python
x = [sqrt(4.0/3*sigma_/alpha_),-0.5*pi]
print "Reference solution = ", x
```

```
Reference solution =  [1.1547005383792515, -1.5707963267948966]
```

We show that the residual is indeed (close to) zero

```python
residual = f(x_, params_)
print "residual = ", residual
```

```
residual =  [2.498e-15, 5.04048e-15]
```

```python

for i in range(1):
  assert(abs(x_[i]-x[i])<1e-6)
```

Solver statistics

```python
print s.stats()
```

```
{}
```