WROCLAW UNIVERSITY OF TECHNOLOGY
DEPARTMENT OF ELECTRONICS

FIELD: Electronics
SPECIALITY: Advanced Applied Electronics

Optimization Methods: Nonlinear Equations

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GRADE:

WROCŁAW 08.06.2017

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Chapter 1

Solution to the given problems

Problem 1: Show that the following system of nonlinear equations:

$$F_1(\mathbf{x}) = x_1^3 + 3x_1^2 + 3x_1 - x_2 = 0,$$
$$F_2(\mathbf{x}) = x_1^2 + 2x_1 - x_2 + 1 = 0,$$

has the global minimum at $x^* = [0.46557 \quad 2.1479]^T$, the local minimum at $x_1 = [-1 \quad -0.5]^T$, and the saddle point at $x_2 = \left[-\frac{1}{3} \quad -\frac{7}{54}\right]^T$.

In general, the unconstrained nonlinear least squares problem is equivalent to:

$$\min_x \sum_{i=1}^{N} F_i^2(x)$$

with the objective function:

$$f(x) = \frac{1}{2}\sum_{i=1}^{N} F_i^2(x)$$

In the case of the following task, objective function will be

$$\begin{aligned}
f(x) &= \frac{1}{2}(F_1^2 + F_2^2) \\
&= \frac{1}{2}[(x_1^6 + 6x_1^5 + 15x_1^4 - 2x_1^3x_2 + 18x_1^3 - 6x_1^2x_2 + 9x_1^2 - 6x_1x_2 + x_2^2) \\
+ &\quad (x_1^4 + 4x_1^3 - 2x_1^2x_2 + 6x_1^2 - 4x_1x_2 + 4x_1 + x_2^2 - 2x_2 + 1)] \\
&= \frac{1}{2}(x_1^6 + 6x_1^5 + 16x_1^4 - 2x_1^3x_2 + 22x_1^3 - 8x_1^2x_2 + 15x_1^2 - 10x_1x_2 + 4x_1 + 2x_2^2 - 2x_2 + 1)
\end{aligned}$$

And the points to check are:

$$\begin{aligned}
x^* &= [0.46557 \; 2.1479]^T \\
x_1 &= [-1 \; - 0.5]^T \\
x_2 &= [-\frac{1}{3} \; - \frac{7}{54}]^T
\end{aligned}$$

Firstly, we can calculate the cost function gradient to verify above–mentioned points:

$$\nabla f(x^*) = 0$$

$$\frac{\delta f(x)}{\delta x_1} = 3x_1^5 + 15x_1^4 + 32x_1^3 - 3x_1^2 x_2 + 33x_1^2 - 8x_1 x_2 + 15x_1 - 5x_2 + 2$$
$$\frac{\delta f(x)}{\delta x_2} = -x_1^3 - 4x_1^2 - 5x_1 + 2x_2 - 1$$

And in fact, the mentioned in task description points are recognized as a solutions of the cost function gradient.

To check their nature, we need to calculate the Hessian and evaluate it according to the stationary points.

$$\nabla^2 f(x) = \begin{bmatrix} \frac{\delta^2 f(x)}{\delta x_1^2} & \frac{\delta^2 f(x)}{\delta x_1 x_2} \\ \frac{\delta^2 f(x)}{\delta x_1 x_2} & \frac{\delta^2 f(x)}{\delta x_2^2} \end{bmatrix}$$

$$\nabla^2 f(x) = \begin{bmatrix} 15x_1^4 + 60x_1^3 + 96x_1^2 - 6x_1 x_2 + 66x_1 - 8x_2 + 15 & -3x_1^2 + 8x_1 + 5 \\ -3x_1^2 + 8x_1 + 5 & 2 \end{bmatrix}$$

$$for\ point\ [0.46557\ 2.1479] = \begin{bmatrix} 50.11 & -9.37 \\ -9.37 & 2 \end{bmatrix}$$
$$det > 0, M1 > 0, f(x) = 5.01e - 11,\ there\ is\ a\ minimum\ (global)$$

$$for\ point\ [-1\ \ -0.5] = \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix}$$
$$det > 0, M1 > 0, f(x) = 0.25,\ there\ is\ a\ minimum$$

$$for\ point\ [-\frac{1}{3}\ \ -\frac{7}{54}] = \begin{bmatrix} 2.41 & -2.66 \\ -2.66 & 2 \end{bmatrix}$$
$$det < 0, M1 > 0, f(x) = 0.33,\ there\ is\ a\ saddle\ point$$

To make all the calculations above, the following script in Python was written to perform symbolic computations:

```
#!/usr/bin/python

from sympy import diff, Symbol, latex, Matrix


def optimization(function, x1, x2):

    print latex(function)

    #calculating the gradient's elements
    firstx1 = diff(function, x1)
    firstx2 = diff(function, x2)

    print firstx1.expand()
    print firstx2.expand()


    #calculations for Hessian elements
    secondx1x1 = diff(function, x1, x1)
    secondx1x2 = diff(function, x1, x2)
    secondx2x1 = diff(function, x2, x1)
    secondx2x2 = diff(function, x2, x2)

    print "\n Hessian elements:\n\n"
    print latex(secondx1x1) +"\t" + latex(secondx1x2)
    print latex(secondx2x1) + "\t"+latex(secondx2x2)


    point1 = [0.46557, 2.1479]
    point2 = [-1.0, -0.5]
    point3 = [-1.0/3, -7.0/54]

    point = point3
    print secondx1x1.subs(x1, point[0]).subs(x2, point[1]);
    print secondx1x2.subs(x1, point[0]).subs(x2, point[1]);
    print secondx2x1.subs(x1, point[0]).subs(x2, point[1]);
    print secondx2x2.subs(x1, point[0]).subs(x2, point[1]);
    print "\n\n"
    print function.subs(x1, point[0]).subs(x2, point[1]);


def main():
    x1 = Symbol('x1')
    x2 = Symbol('x2')

    f1 = x1**3 + 3*x1**2 + 3*x1 - x2
    f2 = x1**2+2*x1 -x2 + 1
    f = (f1**2 + f2**2)/2

    function = f.expand()
    optimization(function, x1,x2)

main()
```

Problem 2: Solve the following system of nonlinear equations with the selected nonlinear least squares methods.

$$F_1(\mathbf{x}) = x_1^3 - 3x_1^2 + 3x_1 - x_2 - 3 = 0,$$
$$F_2(\mathbf{x}) = x_1^2 - 2x_1 - x_2 = 0.$$

Draw the contour lines of the cost function in the nonlinear least square problem. Check the optimality points.

To resolve this nonlinear LS problem, the Newton and Broyden algorithm were used.

```
Newton's Method
iteration =  5

x =
2.4656   1.1479

Elapsed time is 0.000832081 seconds.


Broyden Method
iteration =  424

x =
2.4656 1.1479

Elapsed time is 0.055002 seconds.
```

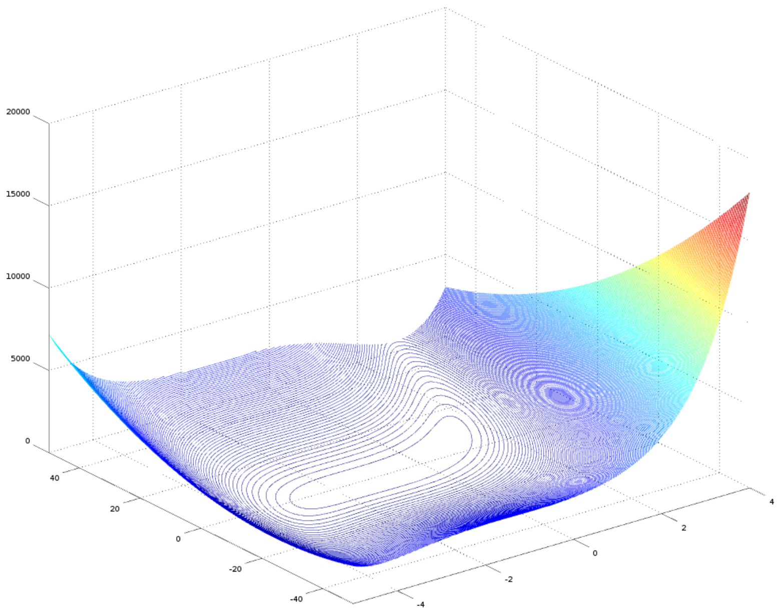

Figure 1.1 Contour plot of cost function.

Problem 3: Solve the following system of nonlinear equations:

$$2x_1 - x_2 = \exp(-x_1),$$
$$-x_1 + 2x_2 = \exp(-x_2),$$

starting from $\mathbf{x}_0 = [-5 \quad -5]^T$.

```
Newton Method
x =
0.56714
0.56714

iter_newton =  8
Elapsed time is 0.00742817 seconds.


Broyden Method
x =
0.56714
0.56714

iter_broyden =  8
Elapsed time is 0.00764704 seconds.
```

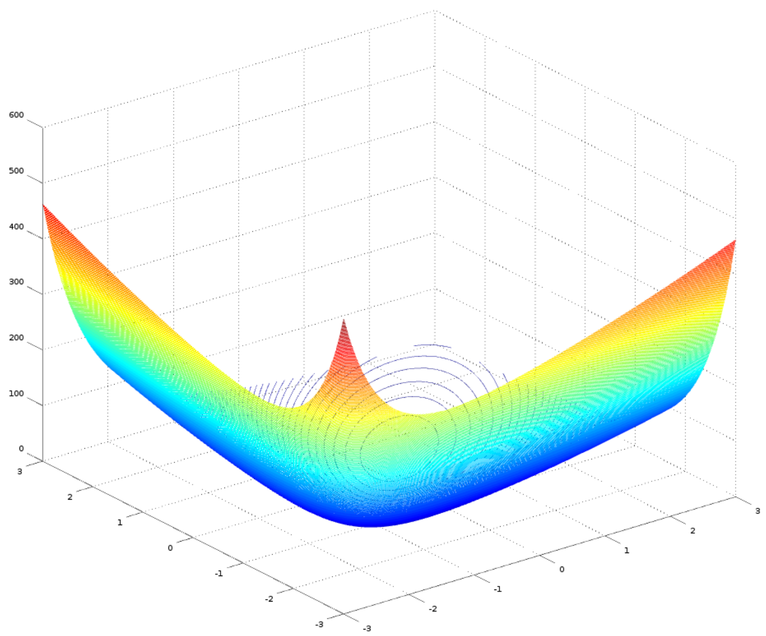

Figure 1.2 Contour plot of cost function

Problem 4: Find $\mathbf{x}$ that minimizes $\sum_{k=1}^{10}\left(2+2k-\exp\left(kx_1\right)-\exp\left(kx_2\right)\right)^2$, starting at the point $\mathbf{x}_0=\left[0.3 \quad 0.4\right]^T$.

To complete this task, the **lsqnonlin** function was used.
In order to make this experiment more interesting, here will be shown its usage in two ways:

- without using Jacobian calculations,
- with Jacobian calculations. It will be turned on using Octave options.

There fore there was prepared two versions of evaluation function to pass to the lsgnonlin:

```
function [F,J] = fun_4(x)
    k = 1:10;
    F = 2 + 2*k-exp(k*x(1))-exp(k*x(2));
endfunction

function [F,J] = fun_4_Jacobian(x)
    k = 1:10;

    F = 2 + 2*k-exp(k*x(1))-exp(k*x(2));

    J = zeros(10,2);
    J(k,1) = -k.*exp(k*x(1));
    J(k,2) = -k.*exp(k*x(2));
endfunction
```

The call end execution looked like this:

```
x0 = [0.3; 0.4];
tic
[x,resnorm,res,eflag, output]= lsqnonlin(@fun_4,x0);
toc


opts = optimset ("Jacobian", "on")
tic
[x,resnorm,res,eflag,output_jacobian] = lsqnonlin(@fun_4_Jacobian,x0
    ,[],[],opts);
toc
```

And the following results were obtained:

```

Calculations without Jacobian:

Elapsed time is 0.0594881 seconds.
x = 0.25803     0.25993

output =
niter =  17
```

```
Calculations with Jacobian

Elapsed time is 0.1645 seconds.
x = 0.25782      0.25823

output_jacobian =
niter =  122
```

As it can be observed, both methods obtained the same values, however Jacobian calculations lasted 3 times more and also performed more iterations (almost 7 times).

Problem 5: The Shockley ideal diode equation is given by: $I = I_s\left(\exp\left\{\frac{U}{n\varphi_T}\right\}-1\right)$. Assuming $I_s = 10^{-10} A$, $n = 1.2$, $\varphi_T = 26 mV$, determine the values of the forward current for the across voltages $U = [0 \quad 0.01 \quad 0.02 \quad \ldots \quad 1]^T$ V. Then solve the inverse problem: having the I-V look-up table, the thermal voltage φ_T, and the Shockley ideal diode equation, try to estimate the reverse bias saturation current I_s and the ideality factor n.

To calculate this task, the model of Shockley diode was coded into a function:

```
function [F]=fun_5_Shockley(x,U)
fi=0.026;

F = x(1) * (exp(U/(x(2)*fi))-1);
end
```

After projection of the data to the **I** current values, it was possible to use Octave curve fitting:

```
x_est = lsqcurvefit(@fun_5_Shockley, x0, Uvalues, Ivalues);
```

The result of curve fitting is quite promising. For x = [1.0540e-09, 1.1924e+00], we obtained:

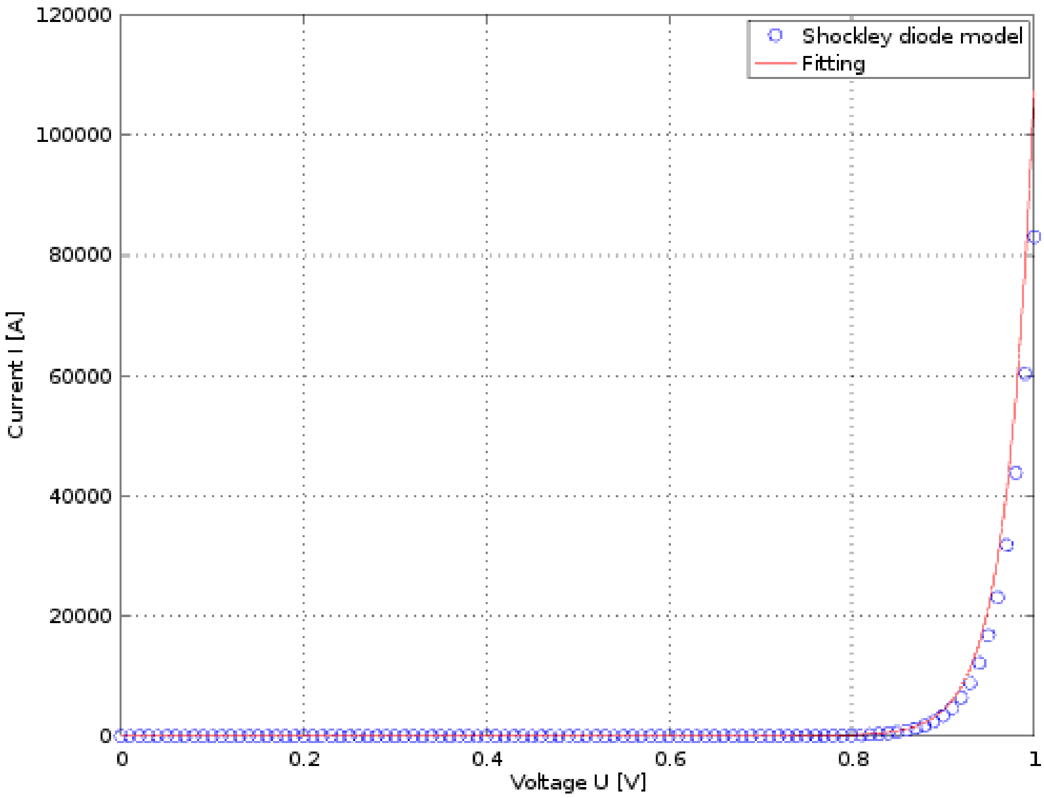

Figure 1.3 Curve fitting (LS) with Octave.

Problem 6: The path loss of the EM wave propagated in a rural area in the distance d (in kilometers) from the base station can be roughly modeled by :

$$L = 128.3 + 32.5 \log d + c, \quad \text{[dB]}$$

where $c \sim N\left(0, \sigma^2\right)$ reflects the effects in attenuation caused by a slow fading. Let $c = 3$ and d= [0.1, 0.2, …, 10] [km], plot the observations L versus d. Then fit the following models

$$y = \alpha + \beta \log d, \qquad \text{(log-distance)}$$
$$y = \alpha + \beta d + \gamma d^2, \qquad \text{(quadratic)}$$
$$y = \alpha + \beta d + \gamma d^2 + \delta d^3, \qquad \text{(cubic)}$$

The following functions to code each model was written:

```
function [F] = fun6_log(x,d)
    alpha = x(1);
    beta = x(2);

    F = alpha + beta * log(d);
end

function F = fun6_quad(x,d)
    alpha = x(1);
    beta = x(2);
    gamma = x(3);

    F = alpha + beta*d + gamma*d.^2;
end

function F = fun6_cubic(x,d)
    alpha = x(1);
    beta = x(2);
    gamma = x(3);
    delta = x(4);

    F = alpha + beta*d + gamma*d.^2 + delta*d.^3;
end
```

The curve fitting process resulted in the following results:

Computed parameters				
Function	α	β	ɣ	δ
Log	131.30000	32.50000		
Quad	102.69010	23.99420	-1.45350	
Cubic	86.07740	43.25453	-6.19728	0.31312

Table. 1.1 Parameters calculated for different models of EM propagation

As the next plots presents, the log model was the best fitting.

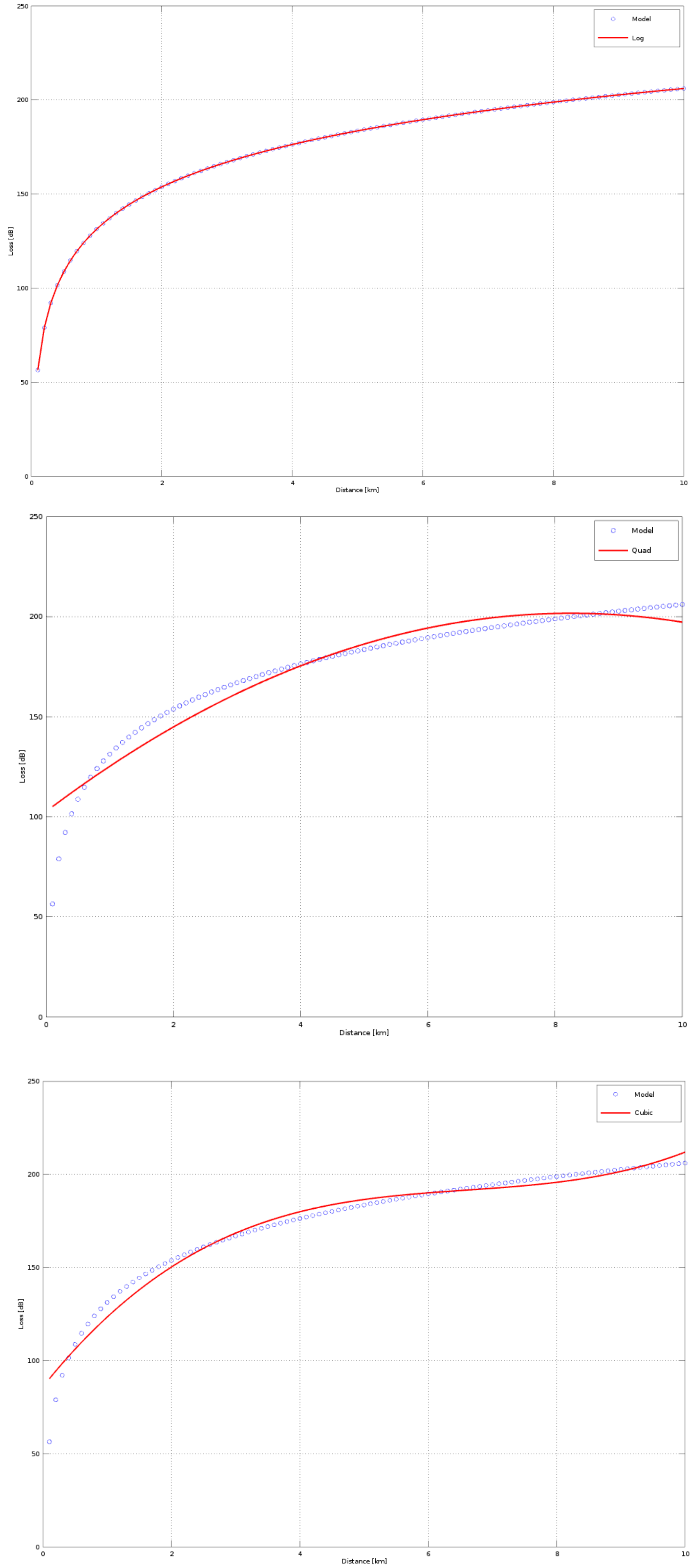

Figure 1.4 Model versus log, quadratic and cubic estimation (from top).

Problem 7: The stability of a particular aircraft in response to the commands of the pilot can be modeled by the following equilibrium equations:

$$F(\mathbf{x}) = \mathbf{A}\mathbf{x} + \phi(\mathbf{x}) = \mathbf{0},$$

where $F : \Re^8 \to \Re^5$, the matrix $\mathbf{A}$ is given by:

$$\mathbf{A} = \begin{bmatrix} -4 & 0.1 & 0.1 & 0 & -10 & 0 & -50 & -8 \\ 0 & -1 & 0 & -23 & 0 & -28 & 0 & 0 \\ 0 & 0 & -0.2 & 0 & 6 & 0 & -1 & -6 \\ 0 & 1 & 0 & -1 & 0 & -0.2 & 0 & 0 \\ 0 & 0 & -1 & 0 & -0.2 & 0 & 0 & 0 \end{bmatrix},$$

and the nonlinear part is defined by:

$$\phi(\mathbf{x}) = \begin{bmatrix} -x_2x_3 + 8x_3x_4 - 500x_4x_5 + 50x_4x_2 \\ x_1x_3 + 0.2x_1x_5 \\ -x_2x_2 - 1.5x_1x_4 + x_2x_4 \\ -x_1x_5 \\ x_1x_4 \end{bmatrix}.$$

The first three variables x_1, x_2, x_3, represent the rates of roll, pitch, and yaw, respectively, while x_4 is the incremental angle of attack and x_5 is the sideslip angle. The last three variables x_6, x_7, x_8 are the controls; they represent the deflections of the elevator, aileron, and rudder, respectively. For a given choice of the control variables x_6, x_7, x_8, determine the behavior of the aircraft modeled by the variables: $x_1, \ldots, x_5$ for each setting of the controls.

Chapter 2

Listings of algorithms

2.1 Coded selected algorithms

Algorithm 1 - Newton algorithm

```
function [x,k] = newton(fun,x,err)
    stop = 2*err;
    iter = 0;
    while stop > err
        [F,J] = fun(x);
        dx = J\(-F);
        x = x+dx;
        [F,J] = fun(x);
        stop = max(abs(F));
        iter = iter + 1;
    endwhile

    iteration = iter
endfunction
```

Algorithm 2 - Broyden method

```
function [xv,it]=broyden(f,x,tol,n)

    fr=zeros(n,1); it=0; xv=x;

    Br=eye(n);
    fr=f(xv);

    while norm(fr)>tol
        it=it+1;
        pr=-Br*fr;
        tau=1;

        xv1=xv+tau*pr;
        xv=xv1;

        oldfr=fr;
        fr=f(xv);

        %Update approximation to Jacobian using Broydens formula
        y=fr-oldfr;
        oldBr=Br;
        oyp=oldBr*y-pr;
        pB=pr'*oldBr;

        for i=1:n
            for j=1:n
                M(i,j)=oyp(i)*pB(j);
            end;
        end;
        Br=oldBr-M./(pr'*oldBr*y);
    end;
endfunction
```

Bibliography

[1] J. Nocedal, S. J. Wright, Numerical Optimization, Springer, 1999,

[2] Zdunek R., Optimization Methods - lecture slides.

[3] Mathworks webpage, ”Unconstrained Optimization Algorithms”, https://www.mathworks.com/help/optim/ug/unconstrained-nonlinear-optimization-algorithms.html

[4] Nonlinear Programming course webpage, North Carolina State University, http://www4.ncsu.edu/ kksivara/ma706/