# Exercises for Week 7

### 1 The Levenberg-Marquardt solution (by hand)

1. Express the solution  $\boldsymbol{p}$  of

$$(J^T J + \lambda I)\boldsymbol{p} = -J^T \boldsymbol{r}$$

in terms of the singular-value decomposition of J and the scalar  $\lambda$ .

2. Express its squared-norm  $\|\boldsymbol{p}\|_2^2$  in these same terms, and show that

$$\lim_{\lambda o 0} oldsymbol{p} = \sum_{\sigma_i 
eq 0} rac{oldsymbol{u}_i^T oldsymbol{r}}{\sigma_i} oldsymbol{v}_i.$$

### 2 The Gauss-Newton method (in Matlab)

Consider a simple problem with n = 1 and m = 2

$$\min_{x \in \mathbb{R}} f(x) = \frac{1}{2}(x+1)^2 + \frac{1}{2}(\lambda x^2 + x - 1)^2,$$

that is, the residual is

$$r(x) = \begin{bmatrix} x+1 \\ \lambda x^2 + x - 1 \end{bmatrix}.$$

- 1. (by hand) Calculate f' and f''. Show that x = 0 is a stationary point for f. Further, show that if  $\lambda < 1$ , then x = 0 is a local minimizer.
- 2. (by hand) Calculate the Jacobian J of f, and check if your calculation is correct according to

$$f'(x) = J(x)^T \boldsymbol{r}(x).$$

3. (in Matlab) Write a Matlab function to compute the residual r and the Jacobian J. You can start this function with

4. (in Matlab) Download the Matlab function GaussNewton\_line and save in the same folder as your Matlab functions written in the previous question. Set  $\lambda=0$  and  $x_0=0.1$ , and turn on the backtracking line search, then call

[xopt,stat] = GaussNewton\_line(@fun\_rJ\_Q2,x0,flag\_line,lambda);

Plot  $e_k = |x_k - 0|$ ,  $|f'(x_k)|$  and  $f(x_k)$  as functions of the iteration number. You should see that your method find the minimizer in one iteration.

- 5. (in Matlab) Set  $\lambda = 0.1$  and  $x_0 = 0.1$  with the backtracking line search. If you plot  $e_{k+1}/e_k$ , can you see that it converges linearly?
- 6. (in Matlab) Set  $\lambda = -2$ ,  $x_0 = 0.1$  and without the line search. Then, what happens now? If we use the backtracking line search, would it become better?

**Explanations:** By substituting J into the Gauss-Newton iteration step and ignore high order terms on x, we will get

$$x_{k+1} = x_k + (\lambda - 1)x_k + O(x_k^2) = \lambda x_k + O(x_k^2).$$

Thus, if  $|\lambda| < 1$ , we will have linear convergence. If  $\lambda < -1$ , the Gauss-Newton method cannot find the minimizer.

### 3 Exponential Fit (in Matlab)

In this exercise, we try to fit the data in data\_exe3.mat with the function

$$\phi(\mathbf{x},t) = x_1 e^{-x_3 t} + x_2 e^{-x_4 t}.$$

1. (by hand) Calculate the Jacobian J of the objective function f for your LSQ data fitting problem

$$\min_{m{x} \in \mathbb{R}^4} f(m{x}) = \frac{1}{2} \|m{r}(m{x})\|_2^2 = \frac{1}{2} \sum_{i=1}^m (y_i - \phi(m{x}, t_i))^2.$$

2. (in Matlab) Write a Matlab function to compute the residual r and the Jacobian J. You can start this function with

- 3. Set  $x_0 = [1, -1, 1, 2]^T$ , and call GaussNewton\_line with the backtracking line search to solve this nonlinear data fitting problem. Plot  $\|\nabla f(x_k)\|_2$  and  $f(x_k)$  as functions of the iteration number. Which solution do you get?
- 4. Change the starting point into  $\mathbf{x}_0 = [3, -3, 3, 3]^T$ , and apply Gauss-Newton method again. What happens now? Why?
- 5. Implement Levenberg-Marquardt method. You can do that by completing the following Matlab code:

function [x,stat] = Levenberg\_Marquardt(fun\_J,fun\_r,x0,varargin)

```
% Solver settings and info
maxit = 100*length(x0);
tol = 1.0e-10;
```

```
stat.iter = 0;
                                  % number of iterations
% Initial iteration
x = x0;
it = 0;
\mbox{\ensuremath{\mbox{\%}}} ----- TODO: Calculate the Jacobian Jx, the residual rx,
                  the function value f and the gradient df.
[rx, Jx] =
f =
df =
converged = (norm(df,'inf') <= tol);</pre>
stat.nfun = 1;
% Initial lambda
lambda = norm(Jx'*Jx,2);
% Store data for plotting
stat.X = x;
stat.F = f;
stat.dF = df;
% Main loop of L-M method
while ~converged && (it < maxit)</pre>
    it = it+1;
    % --- TODO: Calculate the search direction by solving a linear LSQ problem
    A =
    b =
    p = linearLSQ(A,b);
    % --- TODO: Update the iterate
    x_new =
    \% --- TODO: Update the Lagrange parameter lambda
          Save the new residual as rx_new,
    %
          the new Jacobian as J_new
          the new function value as f_new
    % Accept or reject x_new
    if rho > 0
        x = x_new;
        rx = rx_new;
        Jx = Jx_new;
        f = f_{new};
```

```
% --- TODO: calculate the gradient
        df =
    end
    converged = (norm(df,'inf') <= tol);</pre>
    stat.nfun = stat.nfun+1;
    % Store data for plotting
    stat.X = [stat.X x];
    stat.F = [stat.F f];
    stat.dF = [stat.dF df];
end
% Prepare return data
if ~converged
     x = [];
end
stat.converged = converged;
stat.iter = it:
```

6. Set the starting point as  $\mathbf{x}_0 = [3, -3, 3, 3]^T$ , and apply Levenberg-Marquardt method. Does the method converge? If yes, which solution do you get?

Set the last iterate as  $x^*$ , and calculate  $e_k = ||x_k - x^*||_2$ . Plot  $e_{k+1}/e_k$  with respect to k. In the last a few iterations, can you see that the method converge superlinearly?

Plot all data as points and the fit function as a curve. Are you satisfied with your fit function?

# 4 lsqnonlin in Matlab's Optimization Toolbox

- 1. Read about 1sqnonlin using doc 1sqnonlin.
- 2. Read about optimization options using doc optimset.
- 3. See the options by typing optimset() in the command window.
- 4. Use the default setting to solve the data fitting problem in Question 3 with the starting point  $[3, -3, 3, 3]^T$ . Plot the fit function.
- 5. Change the algorithm to 'levenberg-marquardt', and solve the same problem again, and plot the fit function in the same figure.
- 6. Figure out how to supply the Jacobian, J(x), to lsqnonlin. Then, apply the Levenberg-Marquardt method with given J(x) to solve the same problem again, and compare the solution that you obtained with the one in Question 3.6.

(If you really cannot figure out how to supply the Jacobian, you can download Test\_lsqnonlin.m in DTU Inside and see how I would do it.)