

# Optimization Practical Exercise

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# 1 Exercise 1

## 1.1 Linesearch Algorithm with Wolfe-Powell Condition

```
1 function [x_new,f_new,g_new, exit_flag, alpha, eval] = LineSearch (
    f, x_old, f_old, g_old, p, phi_min, alpha_st)
    %Linesearch algorithm with Wolfe-Powell Condition (Algorithm
    4.2)
3
    %Setting of parameters as described in the scriptum
5    tau = 0.1;
    tau1 = 0.1;
7    tau2 = 0.6;
    xi1 = 1;
9    xi2 = 10;
    mu1 = 1/4;
11    mu2 = 0.9;
    sigma = 0.91; %sigma greater than mu1
13
    %if only 6 arguments are given
15    if nargin == 6
        alpha_st = 1;
17    end
19
    alpha_l = 0;
    phi_l = f_old; %phi_l=phi(0)
21    x_old=x_old(:); % x_old always considered as column vector
    dphi_l = dot(g_old,p);
23    exit_flag = 0;
    flag = true; % means that alpha_r is infinity
25    alpha_r = 10^30; %alpha_r should be very large
27
    alpha_tilde = 0; %initialization of alpha_tilde
    eval = 0; %number of evaluations needed
29
    while abs(alpha_r - alpha_l) > 10^(-15)
31        %evaluation of function, gradient and exit_flag
        x_temp = x_old + alpha_st * p;
33        [f_temp, g_temp, exit_flag] = f(x_temp);
        eval = eval + 1;
35
        %function could not be evaluated (alpha_hat not in
        omega_prime)
37        if exit_flag ~= 0
            alpha_r = alpha_st;
39            alpha_st = alpha_l + tau1 * (alpha_r - alpha_l);
41
            %function could be evaluated (alpha_hat in omega_prime)
            else
43                phi_hat = f_temp;
45
                %if function smaller than phi_min, function is declared
                as
                %unbounded
47                if phi_hat < phi_min
                    exit_flag = 2; % output is not minimum
49                    fprintf("Error, unbounded function")
```

```

51         alpha = alpha_st;
        x_new = x_temp;
        f_new = f_temp;
53         return
    end
55     %setting alpha_r and calculating alpha_st
    if phi_hat > (f_old + mul * alpha_st * dphi_l)
57         flag = false; %alpha_r is not infinity
        alpha_r = alpha_st;
59         length = alpha_r - alpha_l;
        c = (phi_hat - phi_l - dphi_l*length)/ (length^2);
61         alpha_tilde = alpha_l - dphi_l/(2*c);
        alpha_st = min(max(alpha_l + tau * length ,
alpha_tilde), alpha_r - tau * length);
63
        else
65             dphi_hat = dot(g_temp,p); %derivative of phi_hat
            %calculating alpha_tilde
67             if dphi_hat < sigma * dphi_l
                if flag
69                     if dphi_l/dphi_hat > (1 + xi2)/xi2
                        alpha_tilde = alpha_st + (alpha_st -
alpha_l) * max(dphi_hat/(dphi_l - dphi_hat), xi1);
71                     else
                        alpha_tilde = alpha_st + xi2 * (
alpha_st - alpha_l);
73                     end
                else
75                     if dphi_l/dphi_hat > 1+(alpha_st-alpha_l)/(
tau2*(alpha_r-alpha_st))
                        alpha_tilde = alpha_st+max((alpha_st-
alpha_l)*dphi_hat/(dphi_l-dphi_hat), tau1*(alpha_r-alpha_st));
77                     else
                        alpha_tilde=alpha_st+tau2*(alpha_r-
alpha_st);
79                     end
                end
81             % setting alpha_l, phi_l, derivative of phi_l and
alpha_st
            alpha_l = alpha_st;
83             phi_l=phi_hat;
            dphi_l = dphi_hat;
85             alpha_st=alpha_tilde;

87             %returning from algorithm
            else
89                 alpha = alpha_st;
                x_new = x_old+alpha*p;
91                 [f_new,g_new,exit_flag] = f(x_new);
                eval = eval+1;
93                 return
            end
95         end
    end
97 end
% final return (if there was no return before)
99 alpha = alpha_st;

```

```

101     x_new = x_old+alpha*p;
        [f_new,g_new,exit_flag] = f(x_new);
        eval = eval+1;
103     end

```

src/LineSearch.m

## 1.2 Method of steepest descent

```

1 function [x,f_val,g,exit_flag, iter, evals] = SteepestDescent (f,
    x0, phi_min,eps,itmax, typ_f,typ_x)
    %Steepest Descent Algorithm for testing LineSearch
3
    %for variable input arguments
5    if nargin < 7
        typ_x(1:length(x0)) = 10^-4;
7    end

9    if nargin < 6
        typ_f = 10^-4;
11    end

13    if nargin < 5
        itmax = 1000;
15    end

17    if nargin < 4
        eps = 10^-6;
19    end

21    if nargin < 3
        phi_min = -10^30;
23    end

25    %starting value for iteration, function value, gradient,
        exit_flag
        xk = x0;
27    [fk,gk,exit_flag] = f(x0);
        evals = 1;
29

31    %iterations of steepest descent
        for iter = 1:itmax

33        %termination condition fullfilled (relative gradient less than
            tolerance)
            if max(abs(gk) .* typ_x / typ_f) <= eps
35                x = xk;
                    f_val = fk;
37                g = gk;
                    return
39            end

41        %calling LineSearch
            [xk,fk,gk,exit_flag,~,eval_temp] = LineSearch(f,xk,fk,gk,-gk,
                phi_min);

```

```

43 typ_f = max(typ_f,abs(fk));
   typ_x = max(typ_x,abs(xk));
45 evals = evals + eval_temp; %updating number of evaluations
end
47
   %Setting output, if termination condition is not fullfilled and
   maximal
49 %number of iterations reached
   x = xk;
51 f_val = fk;
   g = gk;
53 exit_flag = 1;
55 end

```

src/SteepestDescent.m

### 1.3 Testfunctions a) to d)

```

1 function [f_val, g, exit_flag] = f_a(x)
   exit_flag=0;
3   x1=x(1);
   x2=x(2);
5   f_val = 0.5*(x1+x2)^2 + 0.05*(x1-x2)^2;
   g = [1.1*x1 + 0.9*x2; 0.9*x1 + 1.1*x2];
7 end

```

src/f\_a.m

```

1 function [f_val, g, exit_flag] = f_b(x)
   exit_flag=0;
3   x1=x(1);
   x2=x(2);
5   f_val = 100*(x2-x1^2)^2 + (1-x1)^2;
   g = [400*x1*(x1^2-x2) + 2*(x1-1); 200*(x2-x1^2)];
7 end

```

src/f\_b.m

```

1 function [f_val, g, exit_flag] = f_c(x)
   exit_flag=0;
3   n = length(x);
   if min(x)<=0
5       f_val = 10^30; %dummy values
       g = ones(n,1); %dummy values
7       exit_flag = 1;
       return
9   end

11  x=x(:); %transform to column vector
   % (1:n)', x, log(x) column vectors
13  f_val = sum((1:n)'.*x.*log(x)) + 1/sum(x);
   g = zeros(n,1); %column vector
15  for i=1:n

```

```

17         g(i)=i*(log(x(i))+1) - 1/sum(x)^2;
end
end

```

src/f\_c.m

```

function [f_val, g, exit_flag] = f_d(x)
2     exit_flag=0;
   n = length(x);

4     x=x(:);
   v=(1:n)';
6     A=(1/(100*n))*eye(n)+hilb(n);
   xAx = x'*A*x;
8     f_val = (xAx)^2-(x'*A*v)^2;
10    g = 4*xAx*(A*x)-2*(x'*A*v)*A*v;
end

```

src/f\_d.m

## 1.4 Testscript

```

1 diary test1.txt
   diary on
3 disp("Funktion f_a test")

5 [x_val,f_val,g_val,~,iter,evals] = SteepestDescent(@f_a,[10,-3]);
   displayVals(x_val,f_val,g_val,iter,evals);

7 disp("_____")

9 disp("Funktion f_b test")

11 [x_val,f_val,g_val,~,iter,evals]= SteepestDescent(@f_b
   ,[-1,2],[-10^30,10^-6,5000]);
13 displayVals(x_val,f_val,g_val,iter,evals);

15 disp("_____")

17 disp("Funktion f_c test");
   for j = [10 100 1000]
19     fprintf("For n = %d \n",j);
       x0 = 5 * ones(1,j);
21     [x_val,f_val,g_val,~,iter,evals] = SteepestDescent(@f_c,x0
       ,-10^30,10^-9,10000);
       displayVals(x_val,f_val,g_val,iter,evals);

23 end

25

27 disp("_____")

29 disp("Funktion f_d test");

31 for j = [10 100 1000]

```

```

33     fprintf("For n = %d \n",j);
    x0 = zeros(j,1);
    x0(j) = 10*j;
35     [x_val,f_val,g_val,~,iter,evals] = SteepestDescent(@f_d,x0
    ,-10^30,10^-6,10000);
    displayVals(x_val,f_val,g_val,iter,evals);
37
end
39
disp("_____")
41
43 diary off

```

src/testex1.m

With a quick printing function.

```

1 function retval = displayVals (x_val, f_val,g_val,iter,evals)
    if length(x_val) < 11
3         fprintf("Minimum computed at: ");
        x_val
5
7     end

9     disp("Minimum at function f value: ");
    f_val

11    disp("norm of gradient: ");
13    no = norm(g_val);
    no

15    fprintf("with %d iterations and %d function evals \n",iter,
    evals);

17
19 end

```

src/displayVals.m

We get the output

```

1 Funktion f_a test
3 Minimum computed at:
x_val =
5
6     1.0e-05 *
7
8     0.2079
9     -0.1852

11 Minimum at function f value:
13 f_val =
14
15     7.9817e-13

```

```

17 norm of gradient:
19 no =
21     6.4204e-07
23 with 73 iterations and 157 function evals


---


25 Funktion f_b test
26 Minimum computed at:
27 x_val =
29     1.0000
30     1.0000
31 Minimum at function f value:
32 f_val =
33     4.3037e-11
34 norm of gradient:
35 no =
36     6.1783e-06
37 with 4319 iterations and 19493 function evals


---


38 Funktion f_c test
39 For n = 10
40 Minimum computed at:
41 x_val =
42     0.3949
43     0.3811
44     0.3767
45     0.3745
46     0.3731
47     0.3722
48     0.3716
49     0.3712
50     0.3708
51     0.3705
52 Minimum at function f value:
53 f_val =
54     -19.9644
55 norm of gradient:
56 no =
57     7.1634e-08

```



```

73 | with 95 iterations and 328 function evals
75 | For n = 100
77 | Minimum at function f value:
79 |
81 | f_val =
83 |
85 |     -1.8578e+03
87 |
89 | norm of gradient:
91 |
93 | no =
95 |
97 |     2.8699e-06
99 |
101 | with 797 iterations and 3582 function evals
103 | For n = 1000
105 | Minimum at function f value:
107 |
109 | f_val =
111 |
113 |     -1.8412e+05
115 |
117 | norm of gradient:
119 |
121 | no =
123 |
125 |     3.9574e-04
127 |
129 | with 5535 iterations and 30423 function evals

```

---

```

103 | Funktion f_d test
105 | For n = 10
107 | Minimum computed at:
109 |
111 | x_val =
113 |
115 |     0.7074
117 |     1.4125
119 |     2.1185
121 |     2.8354
123 |     3.5448
125 |     4.2462
127 |     4.9424
129 |     5.6360

```

```

117 |     6.3286
119 |     7.1201
121 |
123 | Minimum at function f value:
125 |
127 | f_val =
129 |
131 |     -1.6770e+04
133 |
135 | norm of gradient:
137 |
139 | no =

```

```

0.0436
131 with 10000 iterations and 50003 function evals
133 For n = 100
Minimum at function f value:
135 f_val =
137 -1.0983e+10
139 norm of gradient:
141 no =
143 3.6520e+04
145 with 10000 iterations and 80003 function evals
147 For n = 1000
Minimum at function f value:
149 f_val =
151 -1.0513e+16
153 norm of gradient:
155 no =
157 7.1346e+07
159 with 10000 iterations and 110001 function evals
161

```

src/test1.txt

## 1.5 Interpretation

We can see, that the SteepestDescent works for `f_a` relatively well, while to get a relatively good result for `f_b` we already need  $> 4000$  iterations. `f_c` works quite well, although the number of iterations needed grows fast with increase in dimension size. The algorithm fails to work for `f_d` however for big dimensions.

## 2 Exercise 2

### 2.1 Testfunctions a) to d) with Hessian

```

1 function [f_val, g, H] = f_aH(x)
   x1=x(1);
3   x2=x(2);
   f_val = 0.5*(x1+x2)^2 + 0.05*(x1-x2)^2;
5   g = [1.1*x1+0.9*x2;0.9*x1+1.1*x2];
   if nargin > 2
7       H = [1.1,0.9;0.9,1.1];

```

```

end
9 end

```

src/f\_aH.m

```

1 function [f_val, g, H] = f_bH(x)
    x1=x(1);
3    x2=x(2);
    f_val = 100*(x2-x1^2)^2 + (1-x1)^2;
5    g = [400*x1*(x1^2-x2) + 2*(x1-1); 200*(x2-x1^2)];
    if nargin > 2
7        H = [1200*x1^2 - 400*x2 + 2, -400*x1; -400*x1, 200];
    end
9 end

```

src/f\_bH.m

```

1 function [f_val, g, H] = f_cH(x)
    n = length(x);
3    if min(x)<=0
        f_val = 10^30; %dummy values
        g = ones(n,1); %dummy values
        return
7    end

9    x=x(:); %transform to column vector
    % (1:n)', x, log(x) column vectors
11   f_val = sum((1:n)'.*x.*log(x)) + 1/sum(x);
    g = zeros(n,1); %column vector
13   for i=1:n
        g(i) = i*(reallog(x(i))+1) - 1/sum(x)^2;
15   end
    if nargin > 2
17       h = 2/sum(x)^3;
        H = h*ones(n,n) + diag((1:n)'./x,0);
19   end
end

```

src/f\_cH.m

```

1 function [f_val, g, H] = f_dH(x)
2    n = length(x);

4    x=x(:);
    v=(1:n)';
6    A=(1/(100*n))*eye(n)+hilb(n);
    xAx = x'*A*x;
8    f_val = (xAx)^2-(x'*A*v)^2;

10   if nargin > 1
        g = 4*xAx*(A*x)-2*(x'*A*v)*A*v;
12       if nargin > 2
            H = 4*(2*A*x+(A*x)'+x'*A*x*A)-2*A*v*(A*v)';
14       end
    end
16 end

```

```
end
```

src/f\_dH.m

## 2.2 Tests in Exercise 2

```
1 dfile1 = 'Test1.txt';
2 if exist(dfile1, 'file') ; delete(dfile1); end
3 diary(dfile1)
4 diary on
5
6 options1= optimset('LargeScale','off','GradObj','on');
7 options2= optimset('LargeScale','on','GradObj','on','Hessian','off'
8 );
9 options3= optimset('Algorithm','trust-region','LargeScale','on','
10 'GradObj','on','Hessian','on');
11 options = [options1,options2,options3];
12
13 %(a)
14 disp('=====')
15
16 disp(" (A) ")
17 disp('=====')
18
19 for i=1:length(options)
20     disp(" Testing objective function f_a with options: ")
21     disp(options(i));
22
23     s_a = fminunc(@f_aH,[10,-3],options(i));
24     disp(" Calculated minimizer: ");
25     s_a
26     [fm,g] = f_aH(s_a);
27     disp(" Calculated Minimum value: " + fm);
28     disp(" Norm of gradient at calculated Minimum: " + norm(g));
29 end
30
31 disp('=====')
32
33 disp(" (B) ")
34 disp('=====')
35
36 for i=1:length(options)
37     disp(" Testing objective function f_b with options: ")
38     disp(options(i));
39
40     s_b = fminunc(@f_bH,[-1,2],options(i));
41     disp(" Calculated minimizer: ");
42     s_b
43     [fm,g] = f_bH(s_b);
```

```

41     disp("Calculated Minimum value: " + fm);
42     disp("Norm of gradient at calculated Minimum: " + norm(g));
43 end
44
45 disp
46     ("=====")
47 disp("C")
48 disp
49     ("=====")
50
51 for i=1:length(options)
52     disp("Testing objective function f_c with options: ")
53     disp(options(i));
54
55     disp
56         ("=====")
57
58     s_c1 = fminunc(@f_cH,5*ones(1,10),options(i));
59     disp("Calculated minimizer: ");
60     s_c1
61     [fm,g] = f_cH(s_c1);
62     disp("Calculated Minimum value: " + fm);
63     disp("Norm of gradient at calculated Minimum: " + norm(g));
64
65     s_c2 = fminunc(@f_cH,5*ones(1,100),options(i));
66     [fm,g] = f_cH(s_c2);
67     disp("Calculated Minimum value: " + fm);
68     disp("Norm of gradient at calculated Minimum: " + norm(g));
69
70     s_c3 = fminunc(@f_cH,5*ones(1,1000),options(i));
71     [fm,g] = f_cH(s_c3);
72     disp("Calculated Minimum value: " + fm);
73     disp("Norm of gradient at calculated Minimum: " + norm(g));
74 end
75
76 disp
77     ("=====")
78
79 disp(" (D) ")
80 disp
81     ("=====")
82
83 for i=1:length(options)
84     disp("Testing objective function f_d with options: ")
85     disp(options(i));
86
87     disp
88         ("=====")

```

```

85     s_d1 = fminunc(@f_dH,[ zeros(1,9) ,100],options(i));
      disp(" Calculated minimizer: ")
87     s_d1

89     [fm,g] = f_dH(s_d1);
      disp(" Calculated Minimum value: " + fm);
91     disp(" Norm of gradient at calculated Minimum: " + norm(g));

93     disp
      ("=====")

95     s_d2 = fminunc(@f_dH,[ zeros(1,99) ,1000],options(i));
      [fm,g] = f_dH(s_d2);
97     disp(" Calculated Minimum value: " + fm);
      disp(" Norm of gradient at calculated Minimum: " + norm(g));

99     disp
      ("=====")

101    s_d3 = fminunc(@f_dH,[ zeros(1,999) ,10000],options(i));
103    [fm,g] = f_dH(s_d3);
      disp(" Calculated Minimum value: " + fm);
105    disp(" Norm of gradient at calculated Minimum: " + norm(g));

107    disp
      ("=====")

109    end

111    diary off

```

src/Prog1Ex2.m

## 2.3 Interpretation

## 3 Exercise 3

### 3.1 Interpretation

## 4 Exercise 4

### 4.1 Source Code

```

1  options1 = optimoptions('fminunc','GradObj','off');
   options2 = optimset('GradObj','off');
3
   f = @(x) x(1)+10*max(x(1)^2+2*x(2)^2-1,0);
5  x0=[1,1];
   s1 = fminunc(f,x0,options1)
7  s2 = fminsearch(f,x0,options2)

```

```

9 e1 = norm(s1-[-1,0])
  e2 = norm(s2-[-1,0])

```

src/Prog1Ex4.m

```

>> Prog1Ex4
2
  Local minimum possible.
4
  fminunc stopped because it cannot decrease the objective function
6  along the current search direction.
8
  <stopping criteria details>
10
  s1 =
12
      -0.9997      -0.0168
14
  s2 =
16
      -1.0000      0.0000
18
  e1 =
20
      0.0168
22
  e2 =
24
      4.3007e-05
26

```

src/test4\_1.txt

## 4.2 Solution of fminsearch

When applying `fminsearch` to the problem considering the given non-continuously differentiable function

$$\min_{x \in \mathbb{R}^2} x_1 + 10 \max\{x_1^2 + 2x_2^2 - 1, 0\}$$

we get that  $x = (x_1, x_2) \approx (-0.9997, -0.0168)$  solves the above equation where the exact solution should correspond to the vector  $\bar{x} = (x_1, x_2) = (-1, 0)$ . This implies a numerical error of  $\|x - \bar{x}\| \approx 0.0168$  as can be obtained by the `MATLAB` source code in section 4.1.

## 4.3 Solution of fminunc

If instead of `fminsearch` the `MATLAB` command `fminunc` is applied to the same problem as in section 4.2 we get the result of  $x = (x_1, x_2) \approx (-1.0000, 0.0000)$ .

Consequently, we also get a numerical error much smaller in size and given by  $\|x - \bar{x}\| \approx 4.3007 \cdot 10^{-5}$ .

## 4.4 Interpretation

In the **MATLAB** output it states that **fminsearch** stopped because it cannot decrease the objective function along the current search direction any further. Though, if stopping criteria details are displayed we get the following additional information.

```
1 Optimization stopped because the objective function cannot be
   decreased in the
current search direction. Either the predicted change in the
   objective function,
3 or the line search interval is less than eps.
```

src/test4\_2.txt

Consequently, it must be the case that the simplex search method of **fminsearch** which does not make use of numerical or analytic gradients as the line search algorithm in **fminunc** is not appropriate for the considered problem. On the opposite, **fminunc** estimates according gradients using finite differences and therefore provides an adequate line search interval and ultimately a more reliable result.