

% In-Lecture #3 Assignment related to Homework 5.1 Steepest Descent

% This assignment introduces steepest descent algorithms.

% Please see Fig. 6.15 on page 116 in JSK's *Software Receiver Design* book.

% See [steepest descent slides](#) and [Midterm Problem 2.1 in Spring 2016](#).

% Consider performing an iterative minimization of objective function

% $J(x) = x^2 - 14x + 49 = (x - 7)^2$

% via the steepest descent algorithm (JSK equation (6.5) on page 116).

% $x[k + 1] = x[k] - \mu \left. \frac{dJ(x)}{dx} \right|_{x=x[k]}$

% a. Visualize and analyze the shape of the objective function $J(x)$.

% 1) Plot $J(x)$ for $5 < x < 9$. Give the Matlab code for your answer.

```
x = [5 : 0.01 : 9];  
J = x.^2 - 14*x + 49;  
figure;  
plot(x, J);    %% At end of document
```

% 2) Describe the plot.

% *Answer:* It's a concave up parabola (bowl)

% 3) How many local minima do you see?

% *Answer:* 1 at $x = 7$

% 4) Of the local minima, how many are global minima?

% *Answer:* The local minimum is also a global minimum.

% b. As first step in deriving steepest descent update equation,

% compute the first derivative of $J(x)$ with respect to x .

% *Answer:* $dJ(x)/dx = 2x - 14$

% c. Implement the steepest descent algorithm in Matlab with $x[0] = 5$.

% 1) What value of x did steepest descent reach in 50 iterations with $\mu=0.01$?

% *Answer:* $x = 6.2568$

% 2) What value of x did steepest descent reach in 50 iterations with $\mu=0.1$?

% *Answer:* $x = 7.0$

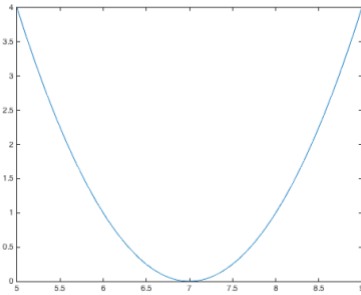
% 3) Is the above value the global minimum of $J(x)$? Why or why not?

% *Answer:* Yes, the objective function has only one minimum.

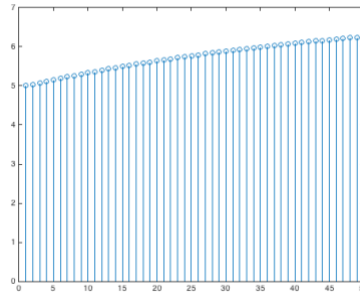
```
% polyconverge.m find the minimum of J(x) via steepest descent  
N=50;                % number of iterations  
mu=0.01;            % algorithm stepsize  
x=zeros(1,N);       % initialize sequence of x values to zero  
x(1)=5.0;           % starting point x(1)  
for k=1:N-1  
    x(k+1)= x(k) - (2*x(k)-14)*mu;    % update equation  
end  
figure;  
stem(x);            % to visualize approximation  
x(N)
```

See plots and epilogue on the next page...

Plots for $\mu = 0.01$

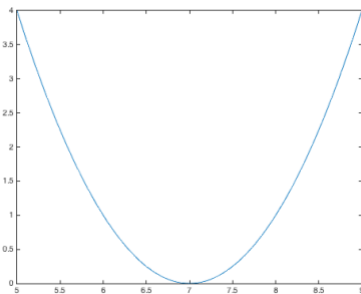


Plot of $J(x)$ vs. x

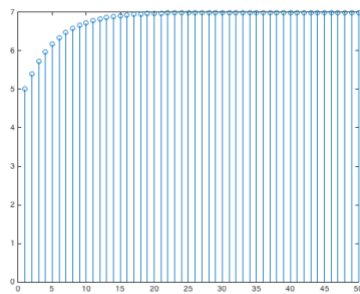


Plot of x vs. iterations

Plots for $\mu = 0.1$



Plot of $J(x)$ vs. x



Plot of x vs. iterations

Convergence. In general, the convergence of the steepest descent algorithm depends on the initial guess and the value of the step size μ .

In this problem, the steepest descent algorithm is a first-order IIR filter with a pole at $1 - 2\mu$:

$$x[k + 1] = (1 - 2\mu)x[k] + 14\mu u[k]$$

The current output is $x[k + 1]$, previous output is $x[k]$, and current input is $14\mu u[k]$ where $u[k]$ is the unit step function. For the first-order IIR filter to be BIBO stable, the pole has to be inside the unit circle, i.e. $-1 < 1 - 2\mu < 1$ or equivalently $0 < \mu < 1$. We choose a small positive value for the step size so that the steepest descent algorithm converges.

The first derivative acts like a highpass filter: As an LTI system, the first derivative is a highpass FIR filter. Recall that the first-order FIR difference filter from homework 1.1(b) and 2.1(b) is a discrete-time approximation of the first derivative and is a highpass filter.

Often in practice, the first derivative is calculated by formula or estimated numerically using measured data, e.g. using a continuous-time analog signal that has been converted to a discrete-time digital signal. The first derivative, as a highpass filter, will amplify high-frequency components of noise and measurement error.

In this problem, **steepest descent** acts like a lowpass filter if the step size is small enough. For a lowpass filter, we want the pole location to be at say 0.9 which would mean a $\mu = 0.05$. By choosing an appropriate μ value, we can equalize the highpass response of the first derivative.