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% gdall_03
% supports Figure 11.4
% gradient descent inversion of  $d(x)=Lm(x)$ ,
% where  $L$  is a linear operator. The gradient of
% error  $dE/dm$  is calculated using the adjoint method
% The linear operator is  $0.1*(D + 2*I)$  where  $D$  is a
% first derivative and  $I$  is an integral

clear all;

% auxiliary variable x
M=101;
N=M;
Dx=1;
x = Dx*[0:M-1]/(M-1);
xmax=max(x);

% a true model function m(x) that is zero at the boundaries
mtrue = sin(4*pi*x/xmax)+0.5*sin(7*pi*x/xmax)+0.25*sin(13*pi*x/xmax);

% plot the true model parameters
figure(1);
clf;
subplot(3,1,1);
hold on;
set(gca, 'LineWidth',3);
set(gca, 'FontSize',14);
plot(x,mtrue,'k-','LineWidth',6);
xlabel('x');
ylabel('m(x)');

% derivative and integral operators
D = (1/Dx)*toeplitz( [1, -1, zeros(1,M-2)]', [1, zeros(1,M-1)] );
I = Dx*toeplitz( ones(M,1), [1, zeros(1,M-1)] );

% data is a linear operator L on the model parameters,  $d=Lm$ 
% where the linear operator contains both a derivative and an integral:
%  $d = 0.1*(dm/dx + 2 * (\text{integral } 0 \text{ to } x) m \text{ to } dm)$ 
L = 0.1*(D + 2*I);
dtrue = L*mtrue;

% plot the data
subplot(3,1,2);
set(gca, 'LineWidth',3);
set(gca, 'FontSize',14);
hold on;
plot(x,dtrue,'r-','LineWidth',3);
xlabel('x');
ylabel('d(x)');

% brute force  $dE/dm$ , to check
%  $m_0 = \text{ones}(M,1)$ ;
%  $d_0 = L*m_0$ ;
%  $E_0 = (dtrue-d_0)'*(dtrue-d_0)$ ;
%  $dEdm = \text{zeros}(M,1)$ ;
%  $Dm=0.00001$ ;
% for  $i=[1:M]$ 
%      $dm = \text{zeros}(M,1)$ ;
%      $dm(i)=Dm$ ;

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%     m1 = mo+dm;
%     d1 = L*m1;
%     E1 = (dtrue-d1)'*(dtrue-d1);
%     dEdm(i) = (E1-Eo)/Dm;
% end
% dEdmA = -2*(L'*(dtrue-do));
% fprintf('dEdm\n' );
% for i=[1:M]
%     fprintf('%d %f %f\n', i, dEdm(i), dEdmA(i) );
% end

% trial solution
mgo = ones(M,1);
subplot(3,1,1);
plot(x,mgo,'g:', 'LineWidth',3);

% maximum iterations
Niter=100000;

% save error history
Ehist = zeros(Niter+1,1);

% error and its gradient at the trial solution
dgo = L*mgo;
Ego = (dtrue-dgo)'*(dtrue-dgo);
dEdmo = -2*Dx*(L'*(dtrue-dgo));
tau=0.5;
c1=0.0001;
alpha=0.9;
Ehist(1) = Ego;

% gradient descent method
for k = [1:Niter]

    v = -dEdmo / sqrt(dEdmo'*dEdmo);

    % backstep
    for kk=[1:10]
        mg = mgo+alpha*v;
        dg = L*mg;
        Eg = (dtrue-dg)'*(dtrue-dg);
        dEdm= -2*(L'*(dtrue-dg));
        if( (Eg<=(Ego + c1*alpha*v'*dEdmo)) )
            break;
        end
        alpha = tau*alpha;
    end

    % change in solution
    Dmg = sqrt( (mg-mgo)'*(mg-mgo) );

    % update
    mgo=mg;
    dgo = dg;
    Ego = Eg;
    dEdmo = dEdm;
    Ehist(k+1) = Ego;

    % plot one intermediate result
    if( k==40 )
        subplot(3,1,1);

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    plot(x,mgo,'g--','LineWidth',3);
end

% terminate on small change
if( Dmg < 1.0e-6 )
    break;
end
end

fprintf('%d iterations\n',k);

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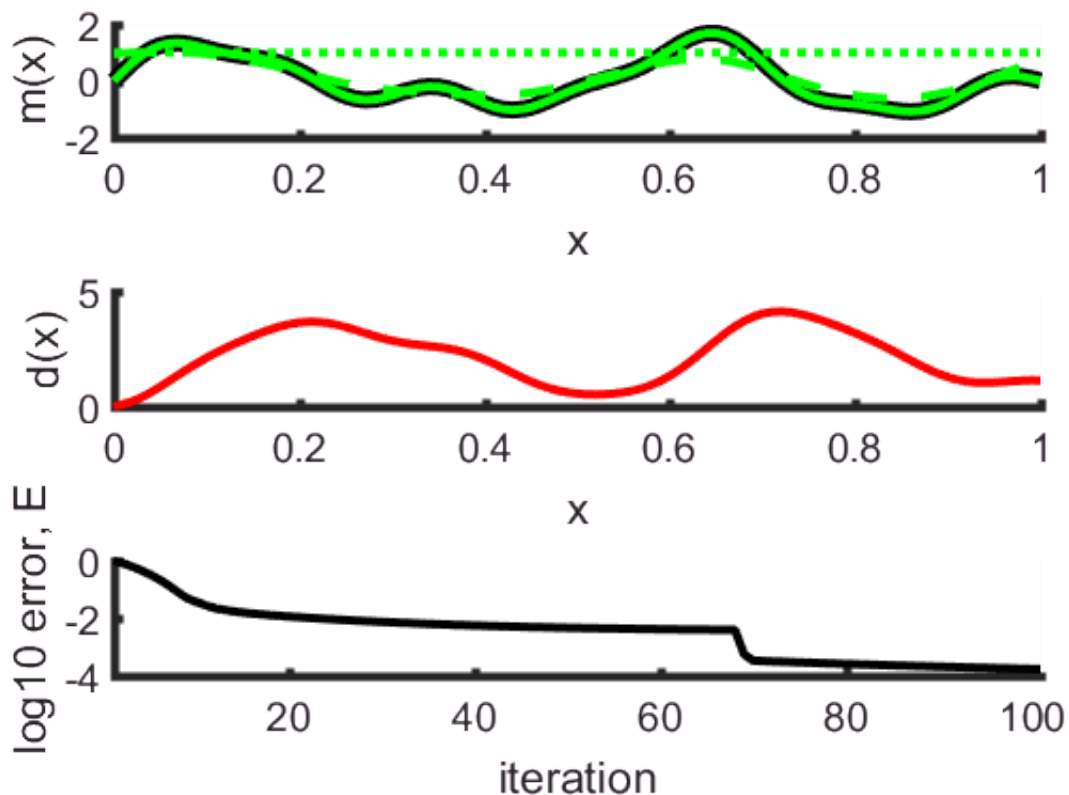
15890 iterations

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% plot result
subplot(3,1,1);
set(gca,'LineWidth',3);
set(gca,'FontSize',14);
plot(x,mgo,'g-','LineWidth',3);

% plot error history
subplot(3,1,3);
set(gca,'LineWidth',3);
set(gca,'FontSize',14);
hold on;
axis( [1, 101, -4, 0] );
plot([1:101],log10(Ehist(1:101)/Ehist(1)),'k-','LineWidth',3);
xlabel('iteration');
ylabel('log10 error, E');

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% Figure 11.5 Example of the solution of a continuous inverse problem using a gradient method

% minimize the error E , where an adjoint method is used to compute ∇E . (A) A test function, m
% (green), trial function (dotted green) reconstructed function after 40 iterations (dashed green)
% and final reconstructed function after 15,890 iterations (green). (B) The data, $d(t)$, satisf
% $d(t) = \mathcal{L}_m(t)$, where \mathcal{L} is the linear operator discussed in the text. (C) Error E as a function
% iteration number, for the first 100 iterations. MatLab script gdall_03.