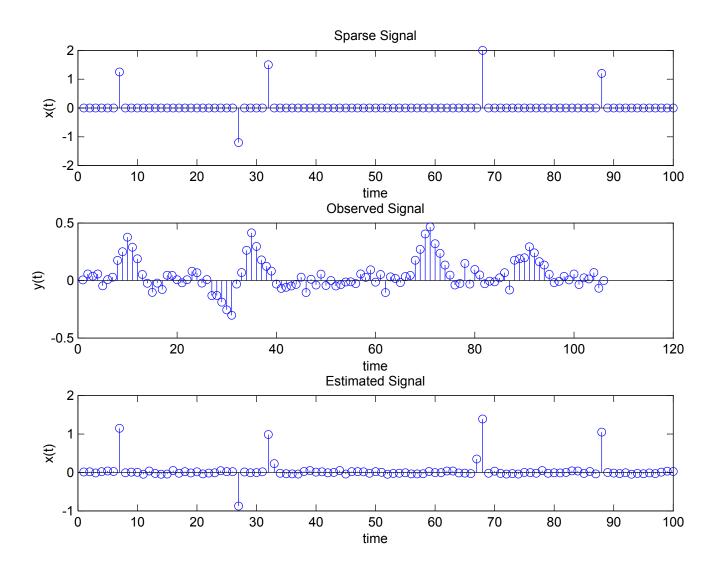
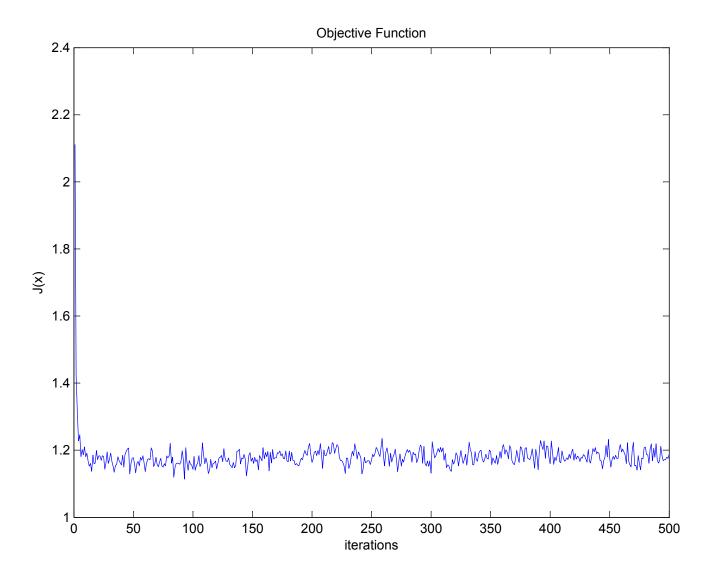
```
>> % Summary Cross Section
>> % Main goal: building/applying fast algorithms for ECG signals approximation
>> % Let's consider an iterative soft (shrinkage) - thresholding algorithm (ISTA)
\gg when assuming an observed signal y = Hx + n is known
\rightarrow % then by minimizing an objective function J(x)
\rightarrow % J(x) = NORM2( y - Hx )^2 + lambda*NORM1(x)
>> % by applying an iterative rule soft() one can find the best matching x
\gg % xk+1 = soft(xk + 2/alphaH'(y-Hxk), lambda/(2alpha))
>> function [x, J] = ista(y, H, lambda, alpha, Nit)
% [x, J] = ista(y, H, lambda, alpha, Nit)
% L1-regularized signal restoration using the iterated
% soft-thresholding algorithm (ISTA)
% Minimizes J(x) = norm2(y-H*x)^2 + lambda*norm1(x)
% INPUT
% y - observed signal
% H − matrix or operator
% lambda - regularization parameter
\% alpha - need alpha >= max(eig(H'*H))
% Nit - number of iterations
% OUTPUT
% x - result of deconvolution
% J − objective function
J = zeros(1, Nit); % Objective function
x = 0*H'*y; % Initialize x
T = lambda/(2*alpha);
for k = 1: Nit
    Hx = H*x;
    J(k) = sum(abs(Hx(:)-y(:)).^2) + lambda*sum(abs(x(:)));
    x = soft(x + (H'*(y - Hx))/alpha, T);
end
end
function [x] = soft(y, T)
x = y - T*sign(y);
end
 function [x, J] = ista(y, H, lambda, alpha, Nit)
Error: Function definitions are not permitted in this context.
>>
```

```
>> % Using the following script we can observe the outcoming results of ISTA
>> clc; clear all; close all;
%-----%
x = zeros(100, 1):
x(7) = 1.25; x(27) = -1.2;
x(32) = 1.5; x(68) = 2;
x(88) = 1.2;
%-------Define-Parameters------%
h = [1 \ 2 \ 3 \ 4 \ 3 \ 2 \ 1]/16; % impulse response
N = 100; % num of samples of x
H = convmtx(h', N); % convolution matrix
lambda = 0.1; alpha = 1; % convergence parameters
Nit = 500; % num of iterations
%-----%
n = 0.05*randn(106, 1);
v = H*x + n:
% Apply ISTA
[x_est, J] = ista(y, H, lambda, alpha, Nit);
figure(1)
% plot sparse signal
subplot(311); stem(x);
xlabel('time'); ylabel('x(t)');
title('Sparse Signal');
% plot observed signal
subplot(312); stem(y);
xlabel('time'); ylabel('y(t)');
title('Observed Signal');
% plot estimated signal
subplot(313); stem(x_est);
xlabel('time'); ylabel('x(t)');
title('Estimated Signal');
figure(2);
% error versus num of iteration
plot(J); xlabel('iterations'); ylabel('J(x)');
title('Objective Function');
```





```
>> % to avoid large matrices computations one could be implemented using function defin
>> function [x, J] = ista_fns(y, H, Ht, lambda, alpha, Nit)
% [x, J] = ista_fns(y, H, lambda, alpha, Nit)

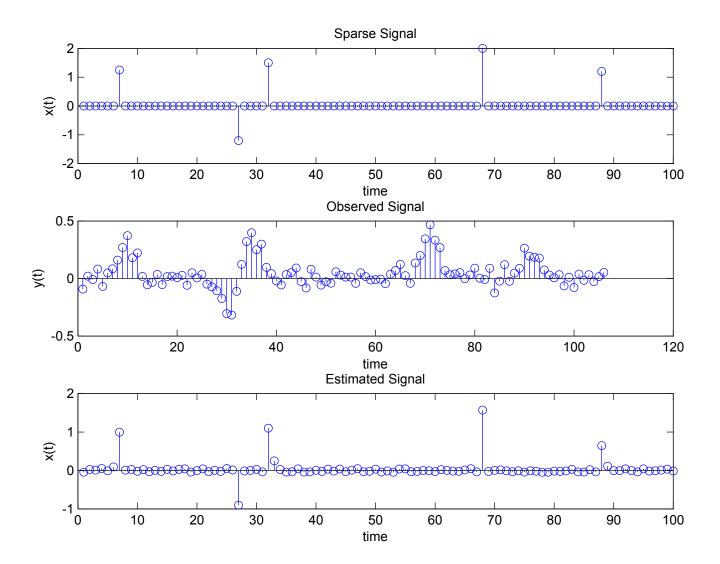
J = zeros(1, Nit); % Objective function
x = 0*Ht(y); % Initialize x
T = lambda/(2*alpha);

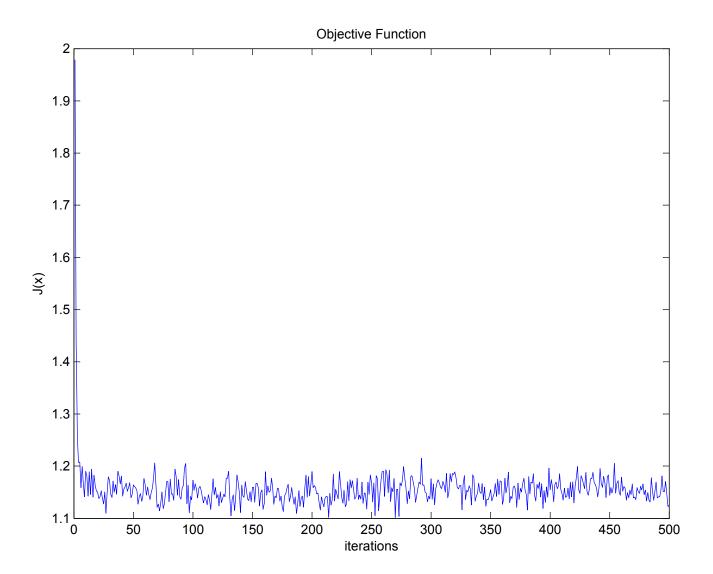
for k = 1:Nit
    Hx = H(x);
    J(k) = sum(abs(Hx(:)-y(:)).^2) + lambda*sum(abs(x(:)));
    x = soft(x + (Ht(y - Hx))/alpha, T);
end

end

function [x] = soft(y, T)
x = y - T*sign(y);
end
```

```
>> % using the following script to test ista fns
>> clc; clear all; close all;
%-----Create-sparse-signal-----
x = zeros(100, 1);
x(7) = 1.25; x(27) = -1.2;
x(32) = 1.5; x(68) = 2;
x(88) = 1.2;
h = [1 \ 2 \ 3 \ 4 \ 3 \ 2 \ 1]/16; \% impulse response
N = 100; % num samples of x
lambda = 0.1; alpha = 1; % convergence parameters
Nit = 500; % num of iterations
H = @(x) conv(h, x); %function implementation instead of matrices
Ht = @(y) convt(h, y);
%-----%
n = 0.05*randn(106, 1);
y = H(x) + n;
% Apply ISTA FNS
[x_{est}, J] = ista_fns(y, H, Ht, lambda, alpha, Nit);
%-----ISTA_FNS-Results-Printout------
figure(1)
% plot sparse signal
subplot(311); stem(x);
xlabel('time'); ylabel('x(t)');
title('Sparse Signal');
% plot observed signal
subplot(312); stem(y);
xlabel('time'); ylabel('y(t)');
title('Observed Signal');
% plot estimated signal
subplot(313); stem(x_est);
xlabel('time'); ylabel('x(t)');
title('Estimated Signal');
figure(2);
% error versus num of iteration
plot(J); xlabel('iterations'); ylabel('J(x)');
title('Objective Function');
```





```
>> % now let's try to match ISTA to our ECG signal
>> % to do that we assume h be of gaussian shape
>> % for a visual example define h:
>> h = [1 \ 2 \ 1]
h =
     1
            2
                   1
>> % normalizing h:
\rightarrow h = h./sum(h)
h =
    0. 2500
                0.5000
                           0.2500
>> % number of samples in h
>> L = length(h)
L =
     3
>> % length of the observed signal y
>> % (also num of rows in convolution matrix)
\gg Ny = 2*L
Ny =
     6
\Rightarrow y = 1:Ny
y =
     1
            2
                   3
                          4
                                 5
                                        6
\rightarrow H = convmtx(h, Ny)
H =
    0.2500
                0.5000
                           0.2500
                                            0
                                                        0
                                                                   0
                                                                               0
                                                                                          0
          0
                0.2500
                           0.5000
                                       0.2500
                                                        0
                                                                   0
                                                                               0
                                                                                          0
          0
                           0.2500
                                       0.5000
                                                  0.2500
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                     0
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          0
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          0
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                                 0
                                                             0.5000
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                                            0
                                                                                          0
          0
                     0
                                 0
                                                             0. 2500
                                                                         0.5000
                                            0
                                                        0
                                                                                    0.2500
>> % guessing vector x
\gg N<sub>X</sub> = L + N<sub>y</sub> - 1
N_X =
     8
```

>> x = 1:Nx

1 2 3 4 5 6 7 8

- >> % Hx_mtx representing each column as h vector shifted in time
- \gg % and multiplied by the corresponding value of x
- \Rightarrow Hx_mtx = H*diag(x)

 $Hx_mtx =$

0. 2500	1. 0000	0. 7500	0	0	0	0	0
0	0. 5000	1. 5000	1. 0000	0	0	0	0
0	0	0. 7500	2. 0000	1. 2500	0	0	0
0	0	0	1.0000	2. 5000	1. 5000	0	0
0	0	0	0	1. 2500	3. 0000	1. 7500	0
0	0	0	0	0	1.5000	3.5000	2.0000

- >> % sum of the columns of the matrix above describes y
- >> % as combinations of shifted gaussians of different amplitudes
- \Rightarrow Hx = H*x(:)

Hx =

2

4

5

6

>> % define corresponding transpose matrix

>> Ht = H'

Ht =

0. 2500	0	0	0	0	0
0.5000	0. 2500	0	0	0	0
0. 2500	0.5000	0. 2500	0	0	0
0	0. 2500	0. 5000	0. 2500	0	0
0	0	0. 2500	0. 5000	0. 2500	0
0	0	0	0. 2500	0. 5000	0. 2500
0	0	0	0	0. 2500	0. 5000
0	0	0	0	0	0. 2500

>> Hty_mtx = Ht*diag(y)

 $Hty_mtx =$

0. 2500	0	0	0	0	0
0.5000	0.5000	0	0	0	0
0. 2500	1. 0000	0. 7500	0	0	0
0	0.5000	1. 5000	1. 0000	0	0
0	0	0. 7500	2. 0000	1. 2500	0
0	0	0	1. 0000	2. 5000	1. 5000
0	0	0	0	1. 2500	3. 0000

0 0 0 0 1.5000

>> Ht*y(:)

ans =

0. 2500

1.0000

2.0000

3.0000

4.0000

5.0000

4. 2500

1.5000

 \Rightarrow Ht * (y(:) - Hx)

ans =

-0. 2500

-0.7500

-1.0000

-1.0000

-1.0000

-1.0000

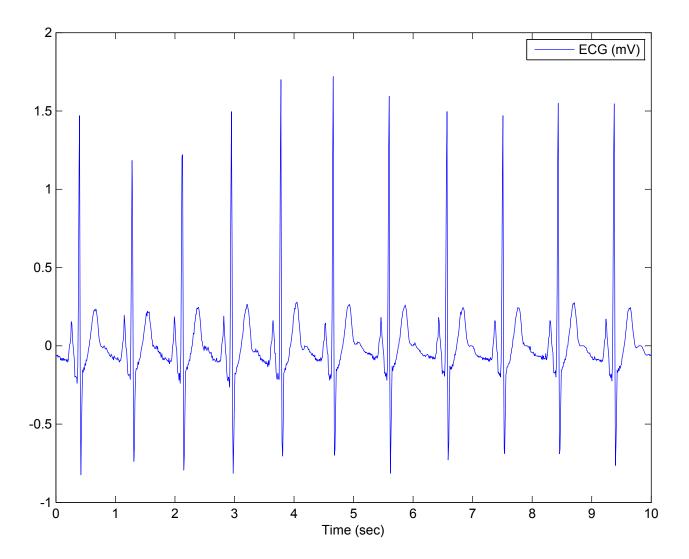
-0. 7500

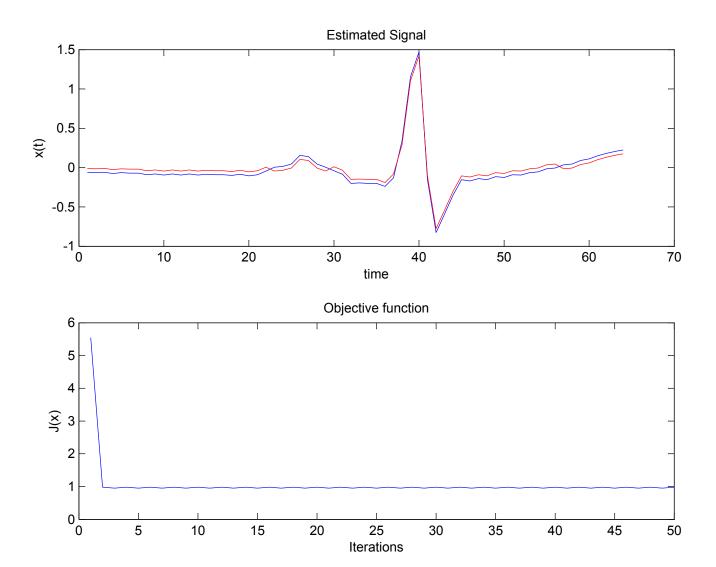
-0. 2500

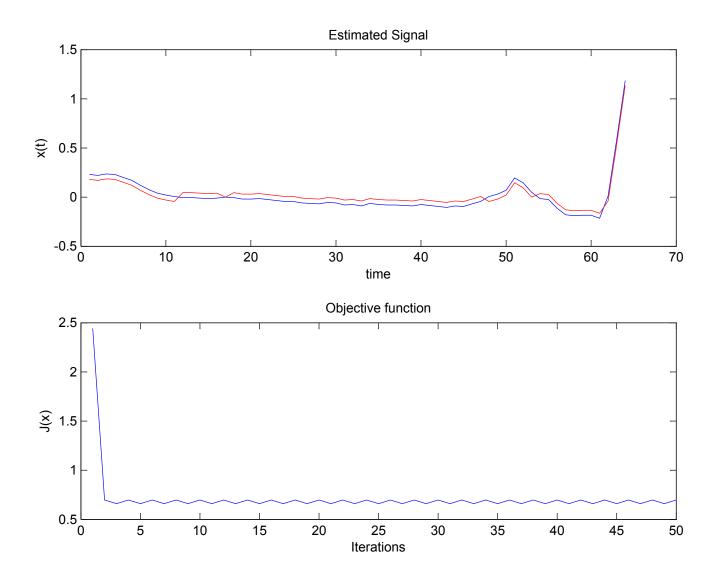
>>

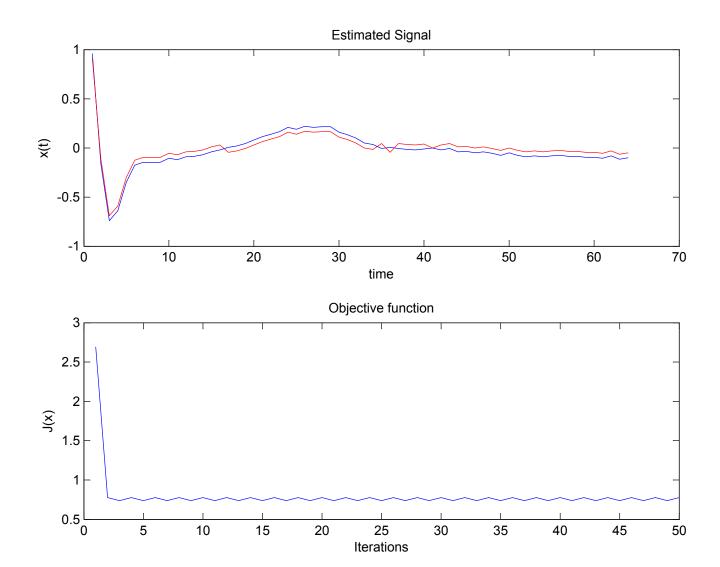
```
>> % now creating a help function as before (ista_ecg.m)
>> function [x, J] = ista_ecg(y, H, lambda, alpha, Nit)
% [x, J] = ista(y, H, lambda, alpha, Nit)
% L1-regularized signal restoration using the iterated
% soft-thresholding algorithm (ISTA)
% Minimizes J(x) = norm2(y-H*x)^2 + lambda*norm1(x)
% INPUT
% y - observed signal
% H − matrix or operator
% lambda - regularization parameter
\% alpha - need alpha >= max(eig(H'*H))
% Nit - number of iterations
% OUTPUT
% x - result of deconvolution
% J - objective functionm
J = zeros(1, Nit); % Objective function
x = 0*H'*y(:); % Initialize x
T = lambda/(2*alpha);
for k = 1: Nit
    Hx = H*x;
    J(k) = sum(abs(Hx(:)-y(:)).^2) + lambda*sum(abs(x(:)));
    x = soft(x(:) + (H'*(y(:) - Hx))./alpha, T);
end
end
function [x] = soft(y, T)
x = y - T*sign(y);
end
```

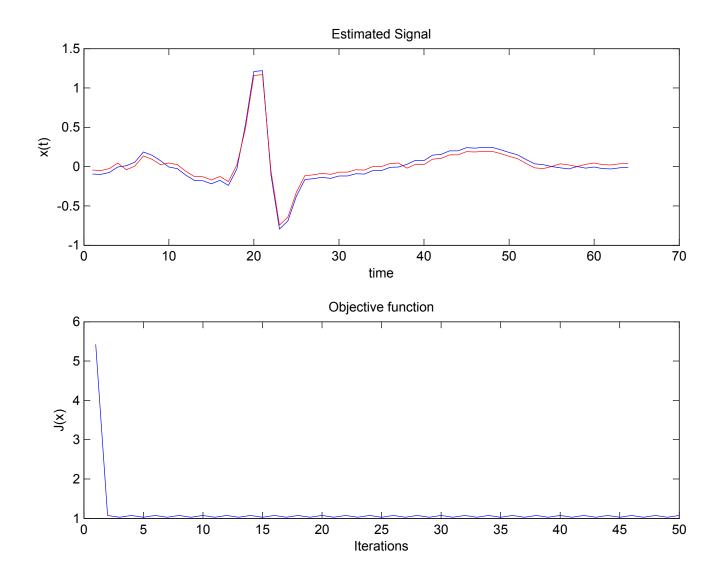
```
>> % using following script to test ISTA (ista ecg test, m)
>> clc; clear all; close all;
%-----Load-Recorded-ECG-----
data a01 = load('a01m.mat');
figure(); Gain = 200;
plotATM('a01m. mat', 'a01m. info');
ecg data = data_a01.val/Gain; % observed signal
%-----Define-Parameters-----
fs = 100; Ts = 1/fs; % data sample rate and duration
L = 2^5; % gaussian shape length in samples
Ny = 2^6; % rows of convolution matrix, y - length
Nx = Ny + L - 1; % rows of convolution matrix, x - length
M = fix(length(ecg data)/Nx); % number of windows
% vector windowing into sections
% y is a matrix with rows of data
[y, padded] = vec2mat(ecg_data, Ny);
% gaussian shape (GS) time window vector
t = -Ts*L/2 : Ts : Ts*(L/2-1); % [sec]
lambda = 0.1; alpha = 1; sig = 0.001; % convergence parameters
Nit = 50; % num of iterations
h = gaussmf(t, [sig 0]); % gaussian impulse response
h = h./sum(h); % normalizing
H = convmtx(h, Ny); % convolution matrix
% windows loop M iterations
%F = zeros(1, length(y)); j = 0;
for i = 1:M
    y in = y(i, :); % pick up corresponding vector
    [x_est, J] = ista_ecg(y_in, H, lambda, alpha, Nit);
    %-----Results-Printout-----
    % plot observed signal
    figure():
    subplot(211); plot(y_in);
    xlabel('time'); ylabel('y(t)');
    title('Observed Signal');
```

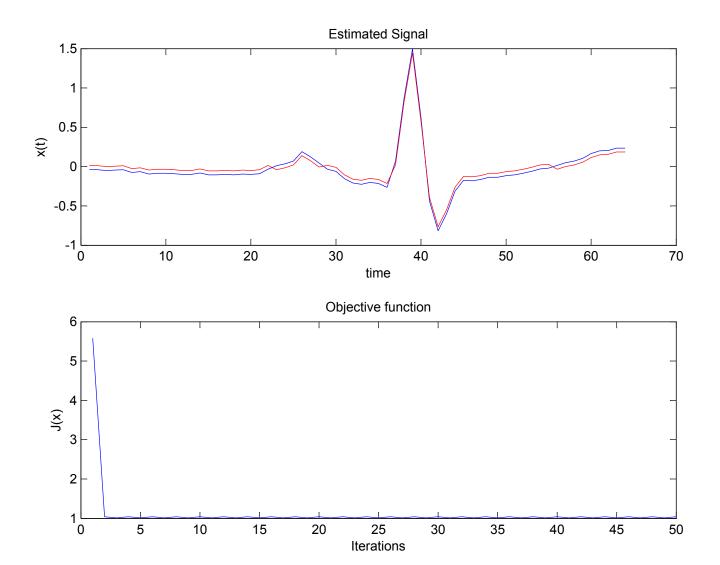


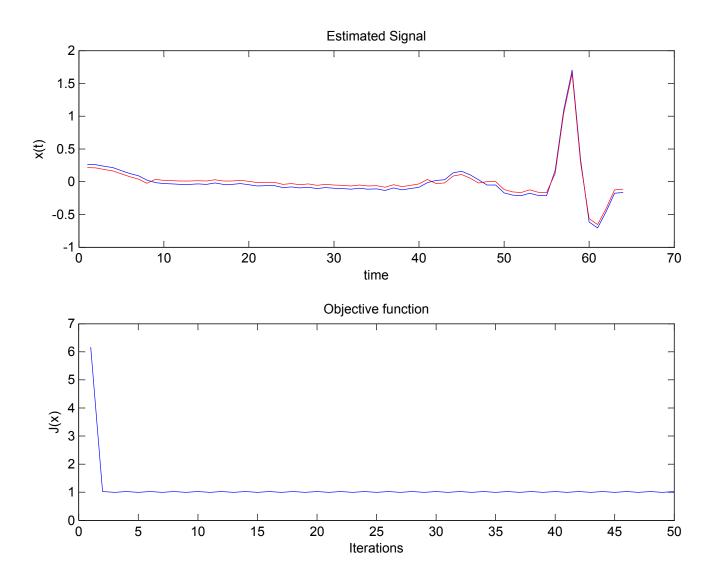


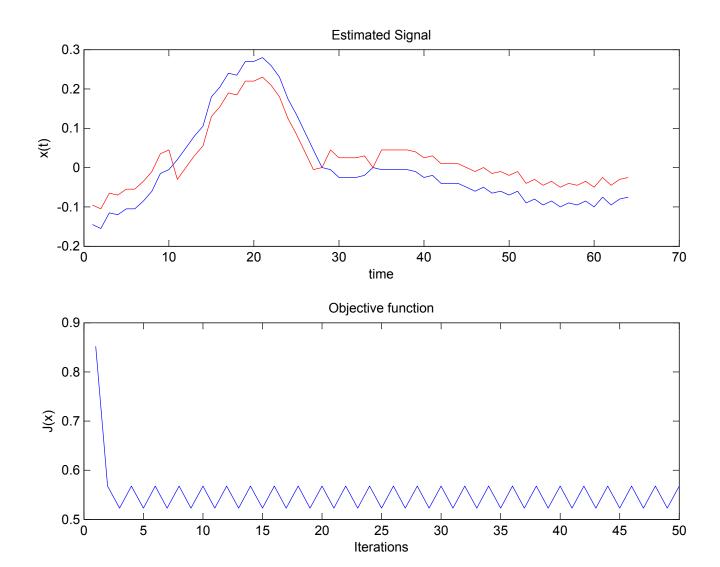


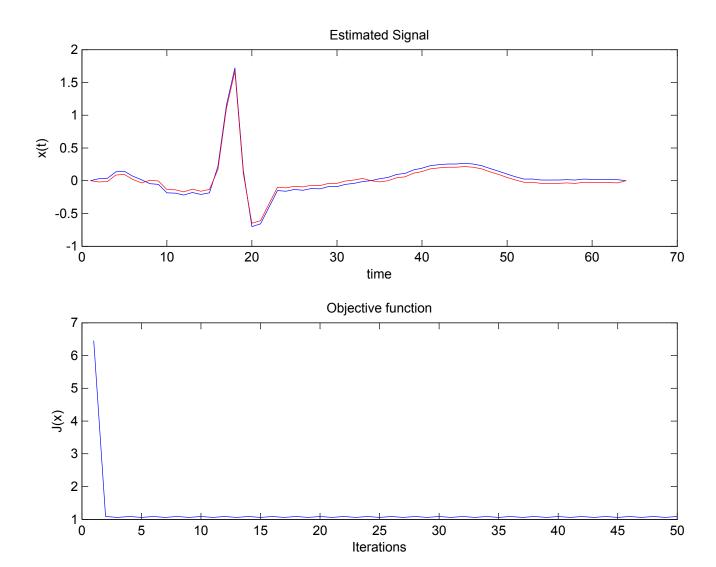


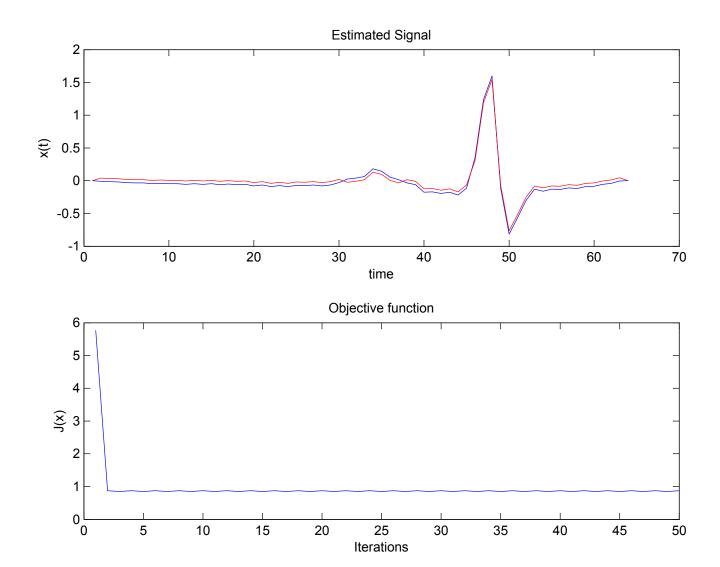


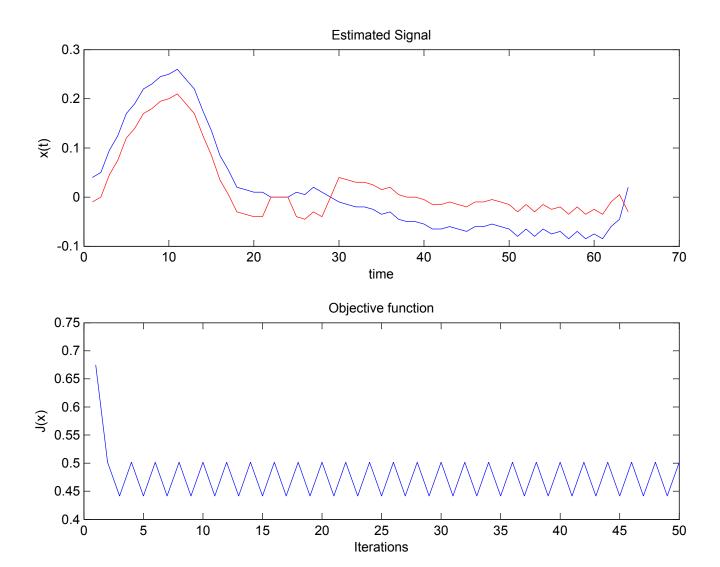












- >> % Notes and remarks:
- >> % observing final results of ECG signal approximation
- \gg % we can notice bad approximation results when peaks are smooth
- >> % due to gaussian span basis with constant sigma parameter
- >> % but on the other hand one can get good results estimating sharp peaks
- >> % Possible solution:
- \gg % find a compromise between amplitudes and sigma parameters for best results \gg