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```
% This small matlab demo tests the Binary Iterative Hard Thresholding algorithm
% developed in:
%
% "Robust 1-bit CS via binary stable embeddings"
% L. Jacques, J. Laska, P. Boufounos, and R. Baraniuk
%
% More precisely, using paper notations, two versions of BIHT are tested
% here on sparse signal reconstruction:
%
% * the standard BIHT associated to the (LASSO like) minimization of
%
%      min || [ y o A(u) ]_- ||_1 s.t. ||u||_0 \leq K      (1)
%
% * the (less efficient) BIHT-L2 related to
%
%      min || [ y o A(u) ]_- ||^2_2 s.t. ||u||_0 \leq K      (2)
%
% where y = A(x) := sign(Phi*x) are the 1-bit CS measurements of a initial
% K-sparse signal x in  $\mathbb{R}^N$ ; Phi is a MxN Gaussian Random matrix of entries
% iid drawn as N(0,1); [s]_-, equals to s if s < 0 and 0 otherwise, is applied
% component wise on vectors; "o" is the Hadamard product such that
% (u o v)_i = u_i*v_i for two vectors u and v.
%
% Considering the (sub) gradient of the minimized energy in (1) and (2),
% BIHT is solved through the iteration:
%
%      x^(n+1) = H_K( x^(n) - (1/M)*Phi'*(A(x^(n)) - y) )
%
% while BIHT-L2 is solved through:
%
%      x^(n+1) = H_K( x^(n) - (Y*Phi)' * [(Y*Phi*x^(n))]_- )
%
% with Y = diag(y), H_K(u) the K-term thresholding keeping the K
% highest amplitude of u and zeroing the others.
%
% Authors: J. Laska, L. Jacques, P. Boufounos, R. Baraniuk
% April, 2011
```

Important parameters and functions

```
N = 2000; % Signal dimension
M = 500; % Number of measurements
K = 15; % Sparsity

% Negative function [. ]_-
neg = @(in) in.*(in < 0);
```

Generating a unit K-sparse signal in \mathbb{R}^N (canonical basis)

```
x0 = zeros(N,1);
rp = randperm(N);
x0(rp(1:K)) = randn(K,1);
x0 = x0/norm(x0);
```

Gaussian sensing matrix and associated 1-bit sensing

```
Phi = randn(M,N);
A = @(in) sign(Phi*in);

y = A(x0);
```

Testing BIHT

```
maxiter = 3000;
htol = 0;

x = zeros(N,1);
hd = Inf;

ii=0;
while(htol < hd)&&(ii < maxiter)
    % Get gradient
    g = Phi'*(A(x) - y);

    % Step
    a = x - g;

    % Best K-term (threshold)
    [trash, aidx] = sort(abs(a), 'descend');
    a(aidx(K+1:end)) = 0;

    % Update x
    x = a;

    % Measure hamming distance to original lbit measurements
```

```

        hd = nnz(y - A(x));
        ii = ii+1;
    end

    % Now project to sphere
    x = x/norm(x);

    BIHT_nbiter = ii;
    BIHT_l2_err = norm(x0 - x)/norm(x0);
    BIHT_Hamming_err = nnz(y - A(x));

```

Testing BIHT-L2

```

maxiter = 3000;
htol = 0;

x_l2 = Phi'*y;
x_l2 = x_l2/norm(x_l2);
hd = Inf;

% Update matrix (easier for computation)
cPhi = diag(y)*Phi;

ii=0;
while (htol < hd) && (ii < maxiter)
    % Compute Gradient
    g = cPhi'*neg(cPhi*x);

    % Step
    a = x_l2 - g;

    % Best K-term (threshold)
    [trash, aidx] = sort(abs(a), 'descend');
    a(aidx(K+1:end)) = 0;

    % Update x_l2
    x_l2 = a;

    % Measure hamming
    hd = nnz(y - sign(cPhi*x));
    ii = ii+1;
end

%Now project to sphere
x_l2 = x_l2/norm(x_l2);

BIHTl2_nbiter = ii;
BIHTl2_l2_err = norm(x0 - x_l2)/norm(x0);
BIHTl2_Hamming_err = nnz(y - A(x_l2));

```

Plotting results

```

figure;
subplot(3,1,1);
plot(x0, 'linewidth', 2);
title('Original signal')

subplot(3,1,2);
plot(x, 'linewidth', 2);
title(sprintf('BIHT reconstruction, L2 error: %e, Consistency score (Hamming error): %i, BIHT iterations: %i', ...
    BIHT_l2_err, BIHT_Hamming_err, BIHT_nbiter));

subplot(3,1,3);
plot(x_l2, 'linewidth', 2);
title(sprintf('BIHT-L2 reconstruction, L2 error: %e, Consistency score (Hamming error): %i, BIHT iterations: %i', ...
    BIHTl2_l2_err, BIHTl2_Hamming_err, BIHTl2_nbiter));

```

