COMPRESSIVE SENSING APPLIED TO HOMELAND SECURITY

Center for Advanced Sensors

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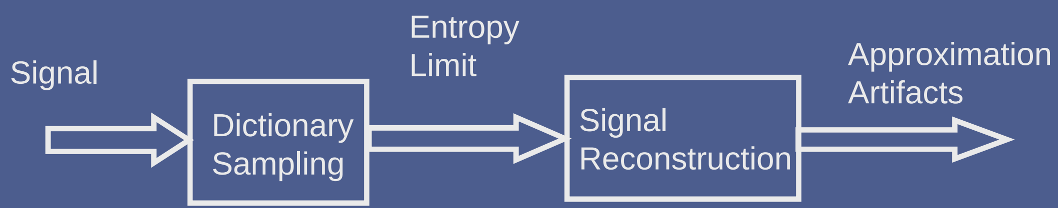
Significance of Compressive Sensing



CS Relative to Homeland Security

Homeland Security Applications are cost conscious

Homeland Security Applications generally must live within commercial safety standards and negotiated treaties

Homeland Security Applications tend to be screening oriented

Homeland Security Applications tend to generate more information faster than can be utilized

Homeland Security Applications tend to overload communication channels

What is required are techniques that allow the handling of large amounts of sensor information without excessive resolution or redundancies

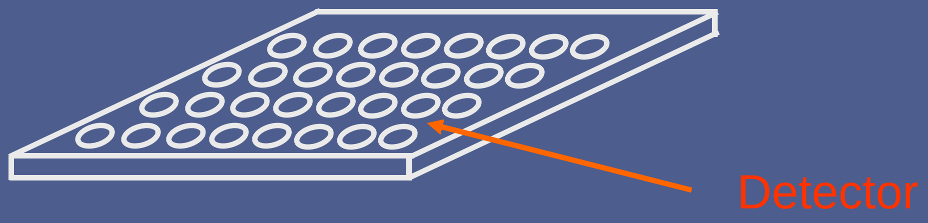
Homeland Security Applications tend to be very situation specific and do not necessarily require a closed, complete solution

The THz FPA Problem

Orientation towards traditional spatial Nyquist Sampling

Wavelength driven resolution limitations are coarse compared to visible but adequate for application

There are a number of practical limitations to the implementation of this density of detectors

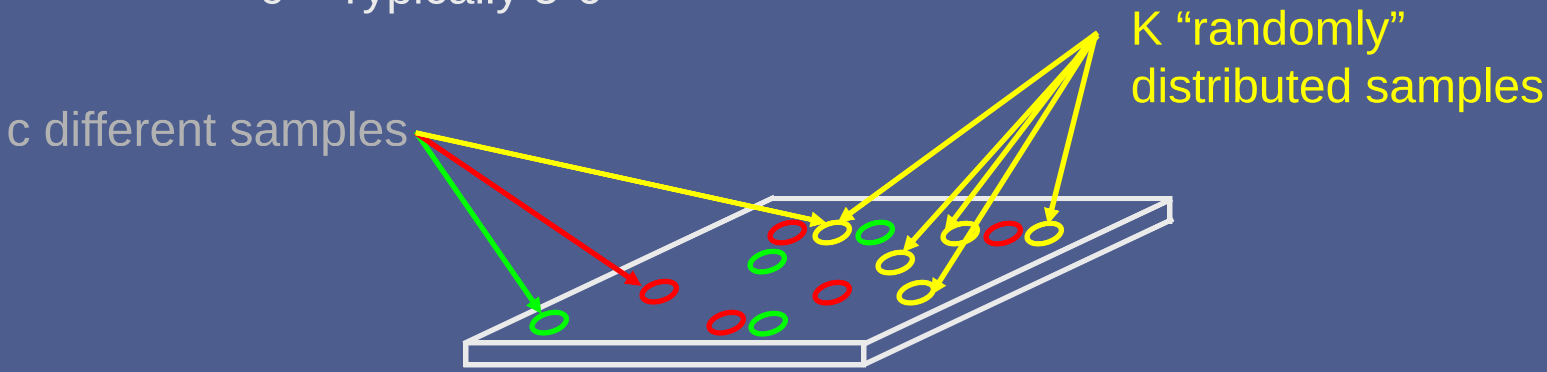


Solution Scheme

cK - "Random" samples required under compressive sensing

K – Sparsity of image set

c – Typically 5-6



Before casting into hardware: How do we know we have chosen an appropriately "random" selection and, in general, do we expect to gain over Nyquist density?

Incoherence Testing

$$0 \le M\left(\Phi_1, \Phi_2\right) = \sup\left\{\left|\left\langle \phi_1, \phi_2 \right\rangle\right| : \phi_1 \in \Phi_1, \phi_2 \in \Phi_2\right\} \le 1$$

If a basis can be found that is sparse for the image set of interest then a new basis set incoherent with the first set exhibits similar properties

Pseudo-random placed detectors can be used (with appropriate signal reconstruction) to the reduce demands on focal plane

The resulting basis set can be tested versus a master basis set

The key question is: What is the master set and does its' sparsity allow this application?

Sample Infrared Image

Locally generated IR image of commercial vehicle

What is the sparsity of typical images of homeland security interest?

Is K small enough to affect complexity reduction in FPA?

Scale reduction without loss of generality

Computational load on computer is significant

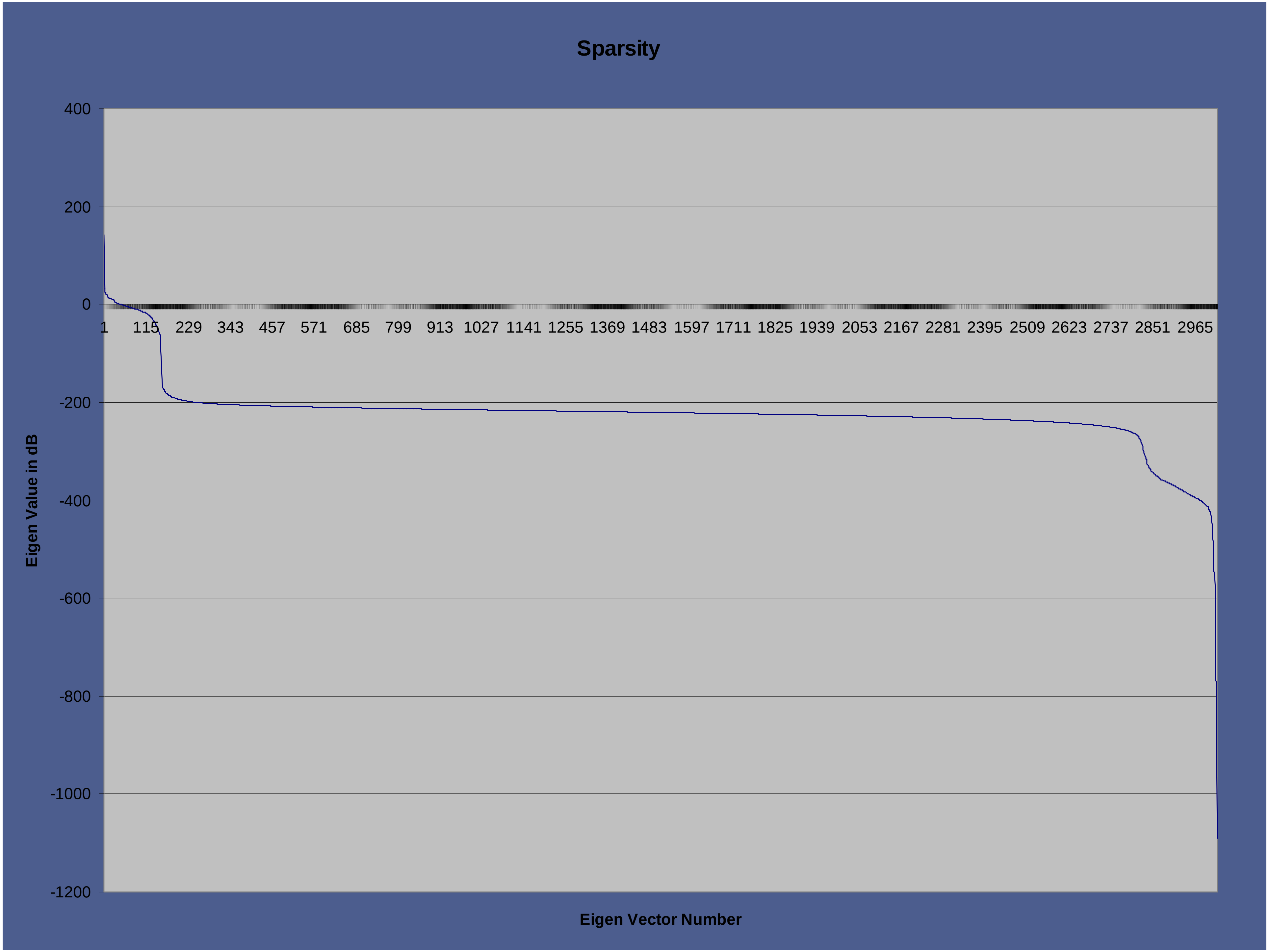
Fortunately it only has to be done once

Once a test basis has been generated a chosen pseudo-random placement need only be compared to test case

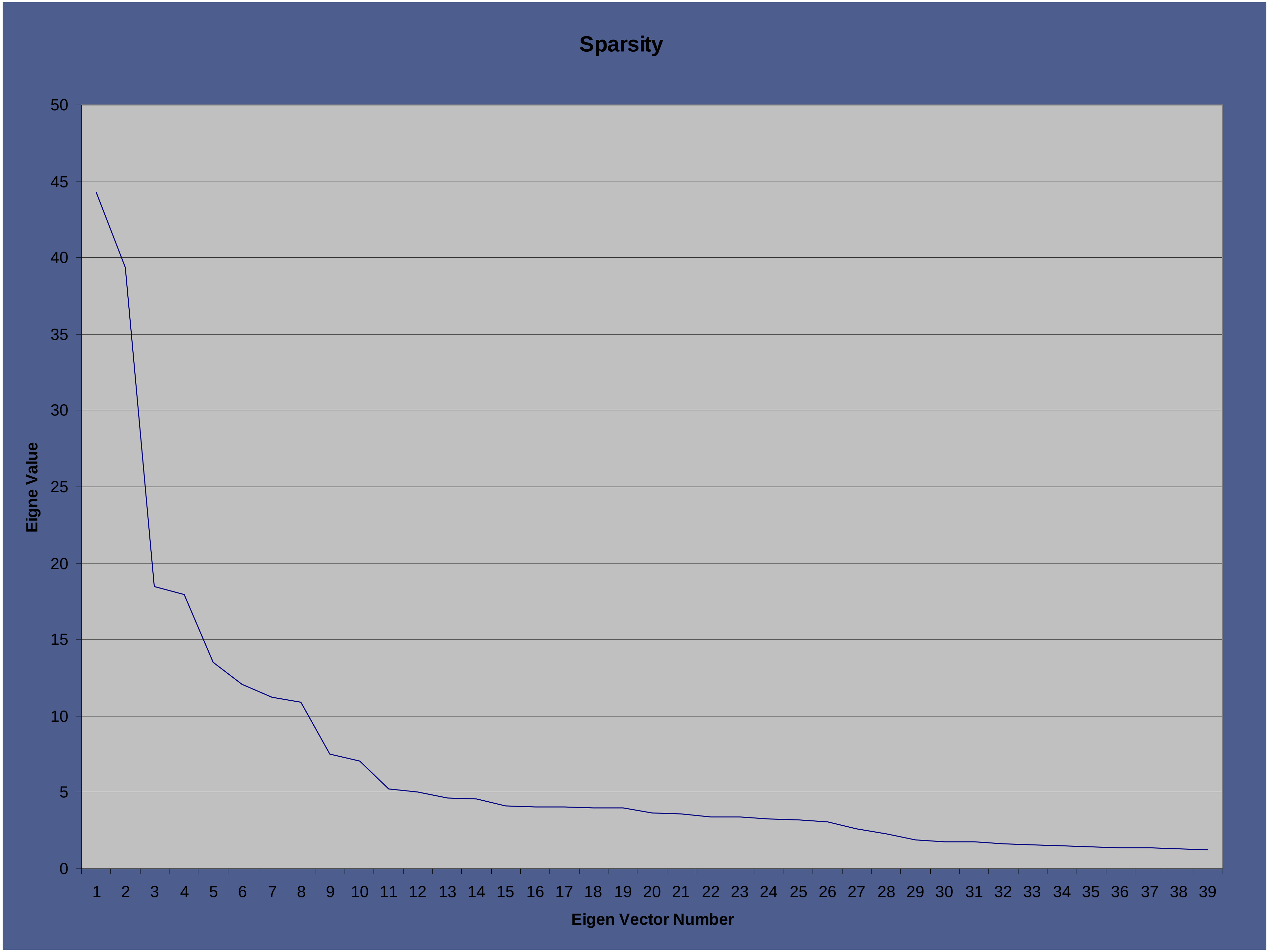
Images from different technologies are of different size

Common reduced scale allows technique development

Fortunately homeland security applications tend to have the detailed object of interest center in the field of view



Sparsity
400
200
0
-200
-400
-600
-800
-1000
-1200
Eigen Value in dB
1
115
229
343
457
571
685
799
913
1027
1141
1255
1369
1483
1597
1711
1825
1939
2053
2167
2281
2395
2509
2623
2737
2851
2965
Eigen Vector Number

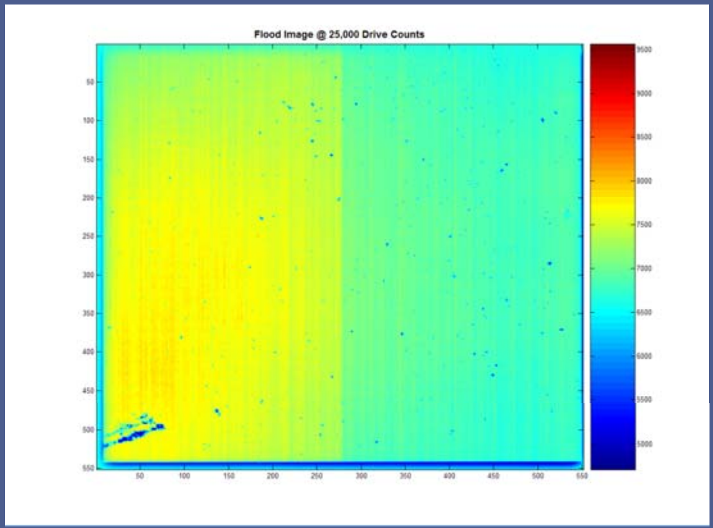

Sparsity
Eigne Value
50
45
40
35
30
25
20
15
10
5
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39
Eigen Vector Number

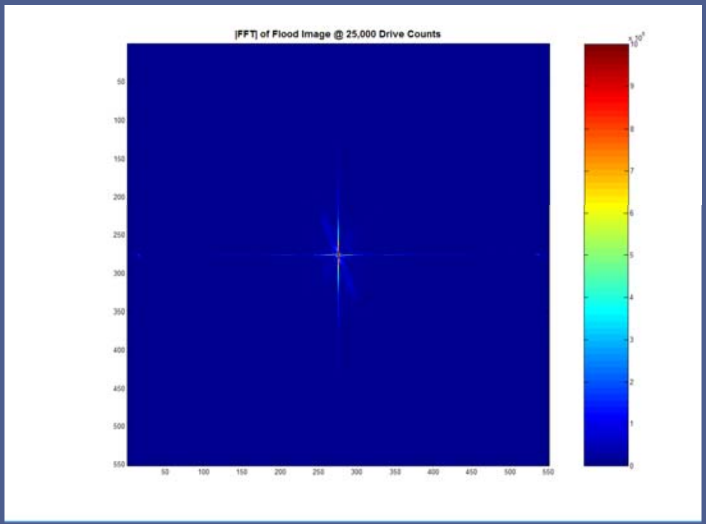
Extension to Field

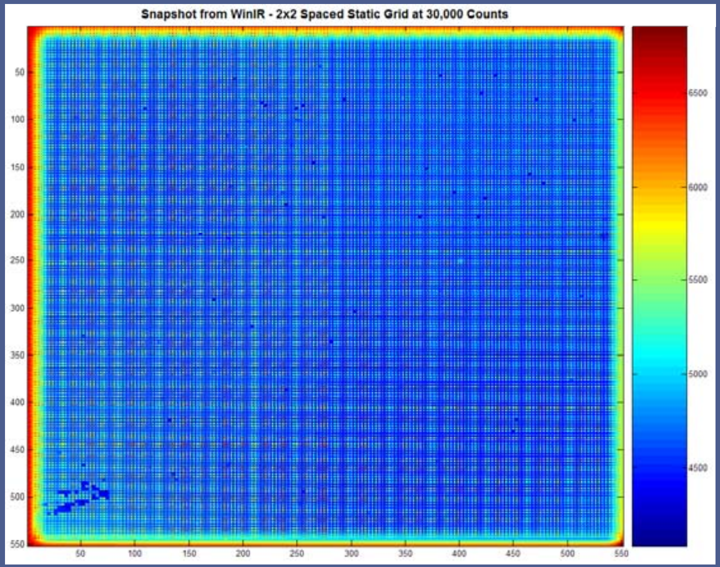
Sparsity demonstrated in actual hardware (with warts and all) via projection simulators

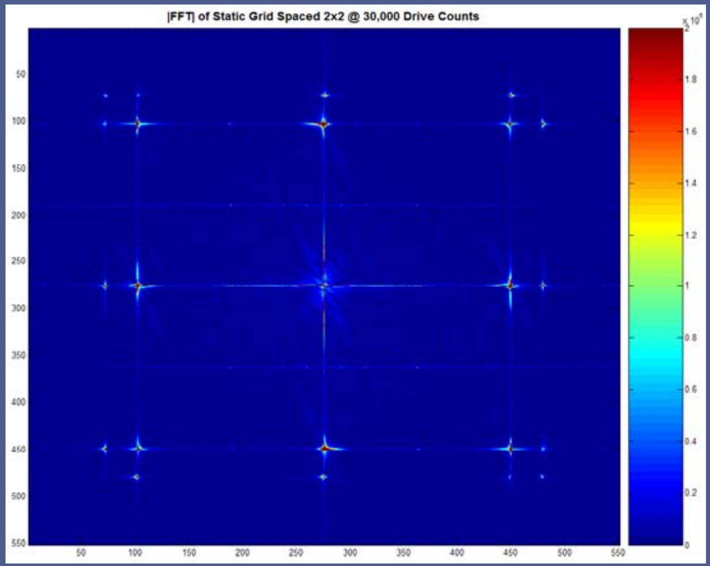
These demonstrations utilize the Fourier Transform which is know to be sparse in smooth signals

Ultimately need generic test basis set and corresponding transform

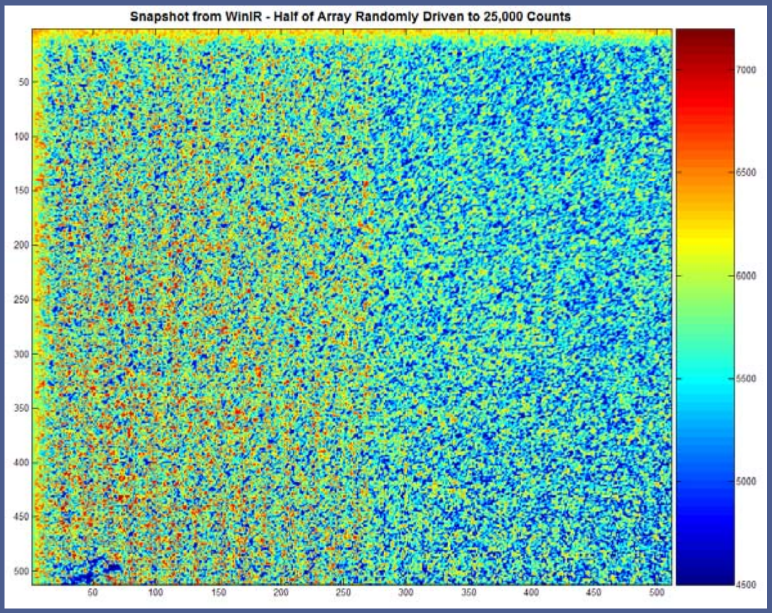


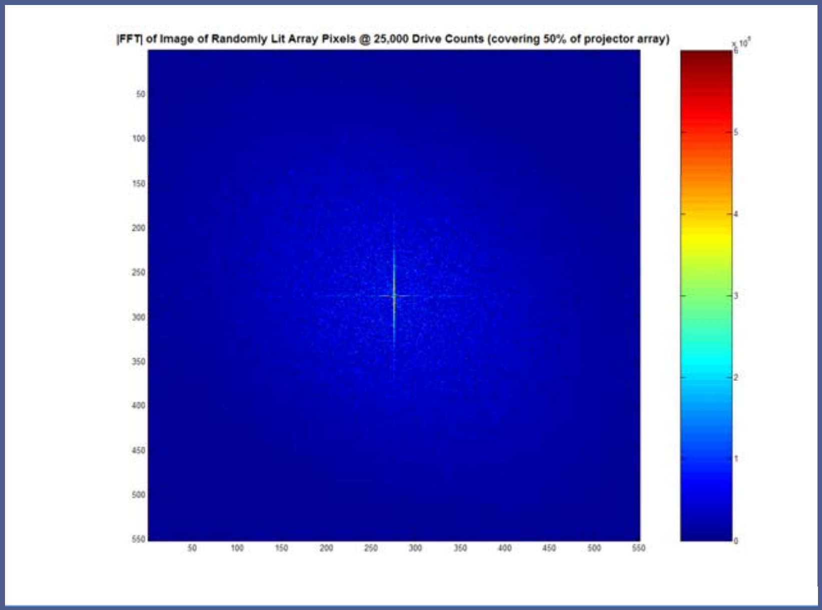






Courtesy Redstone Technical Test Center





Courtesy Redstone Technical Test Center

Karhunen-Loeve Transform as an Expansion Set

$$E[(\overline{X}-\mu_x)(\overline{X}-\mu_x)^T] = \overline{\overline{C}}_{xx} = \overline{\overline{V}}\,\overline{\overline{W}}\,\overline{\overline{V}}^T$$

$$\overline{\overline{V}} = \begin{bmatrix} \overline{E}_1 & \cdots & \overline{E}_n \end{bmatrix}$$

$$\overline{E}_1 = \begin{bmatrix} E_{11} \\ \vdots \\ E_{1n} \end{bmatrix}$$

$$\overline{\overline{W}} = \begin{bmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_n \end{bmatrix}$$

For the i^{th} row and j^{th} column

$$\sum_{k=1}^{n} \lambda_k E_{ki} E_{kj} i = E\{(x_i-\mu_x)(x_j-\mu_x)\}$$

MatLab Code

```
I=imread('Fig1', 'jpg');
imagesc(I);colormap(gray);
d=size(I);
rows=d(1);
cols=d(2);
M=100;
rowsS=round((rows-M)/2)+1;
colsS=((cols-M)/2)+1;
for ii=1:M
   for jj=1:M
      Ir(ii,jj)=I(rowsS-1+ii,colsS-1+jj);
   end
end
figure(2);imagesc(Ir);colormap(gray);
X=zeros(M^2,1);
for ii=1:M
   for jj=1:M
      X((ii-1)*M+jj)=Ir(ii,jj);
   end
end
```

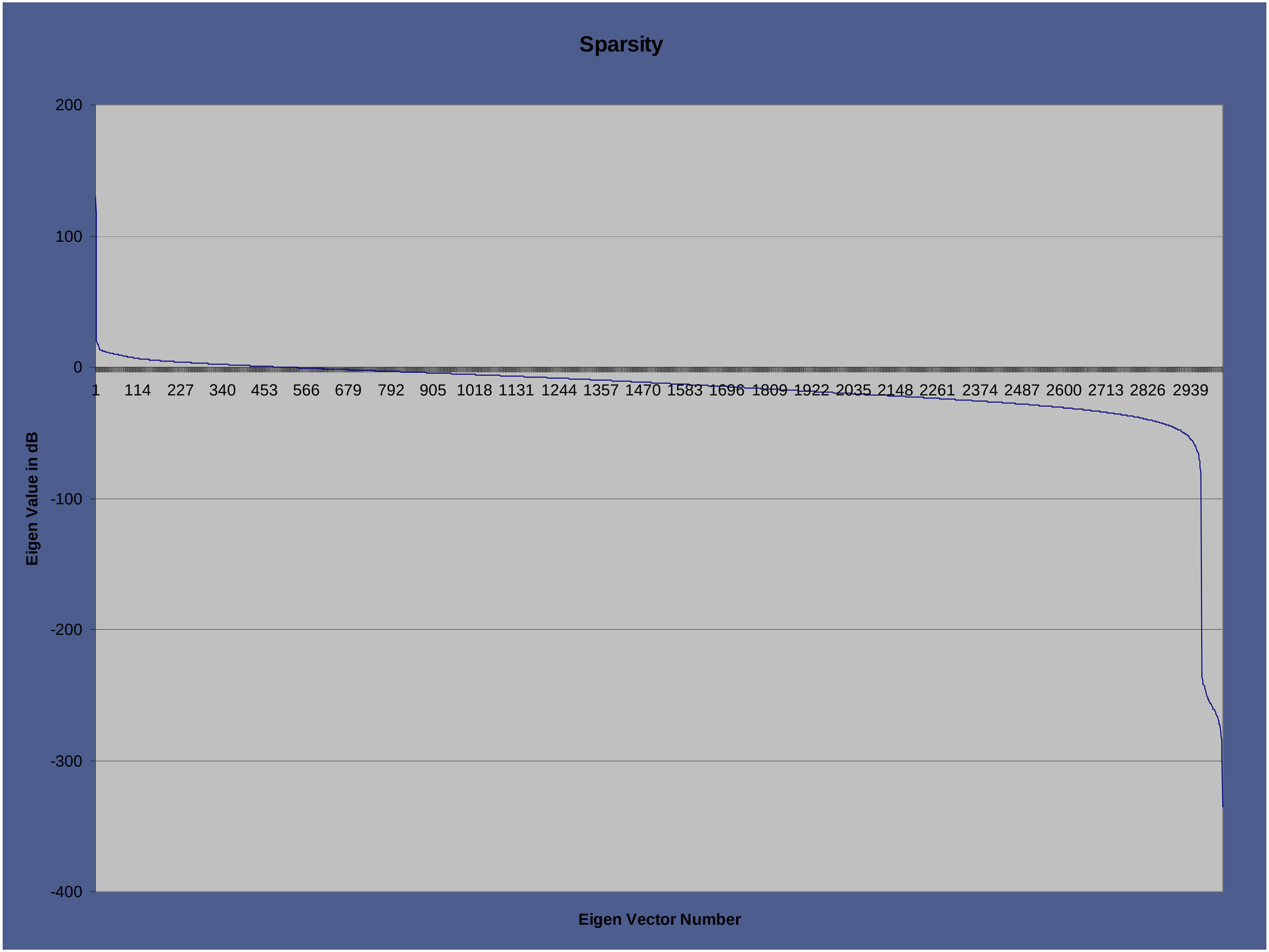
```
Expx=mean(X);
Xr=X-Expx;
for ii=1:M^2
%    display(ii)
   for jj=1:M^2
      sig(ii,jj)=Xr(ii)*Xr(jj);
   end
end
[V D]=eig(sig);
for ii=1:M
   Sp(ii)=D(ii,ii);
end
fgmax=max(Sp);
lfgmax=log10(fgmax);
Spoff=min(abs(Sp))/1E6;
for ii=1:M
   fg(1,ii)=round(Sp(ii)*255/fgmax);
```

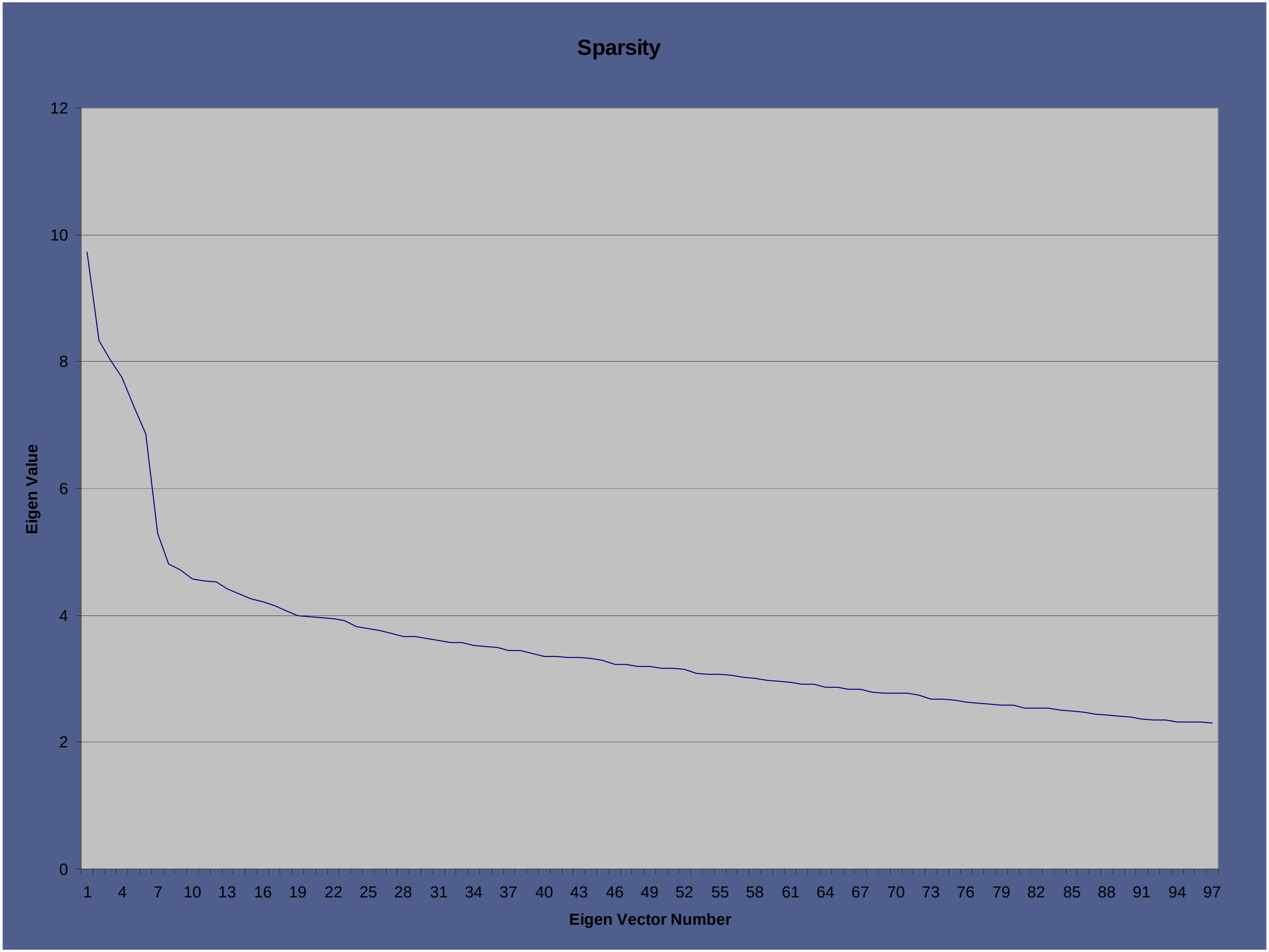
Well Studied Image Set

Standard Image set used for perception experiments

Well characterized and validated for “real world” security application

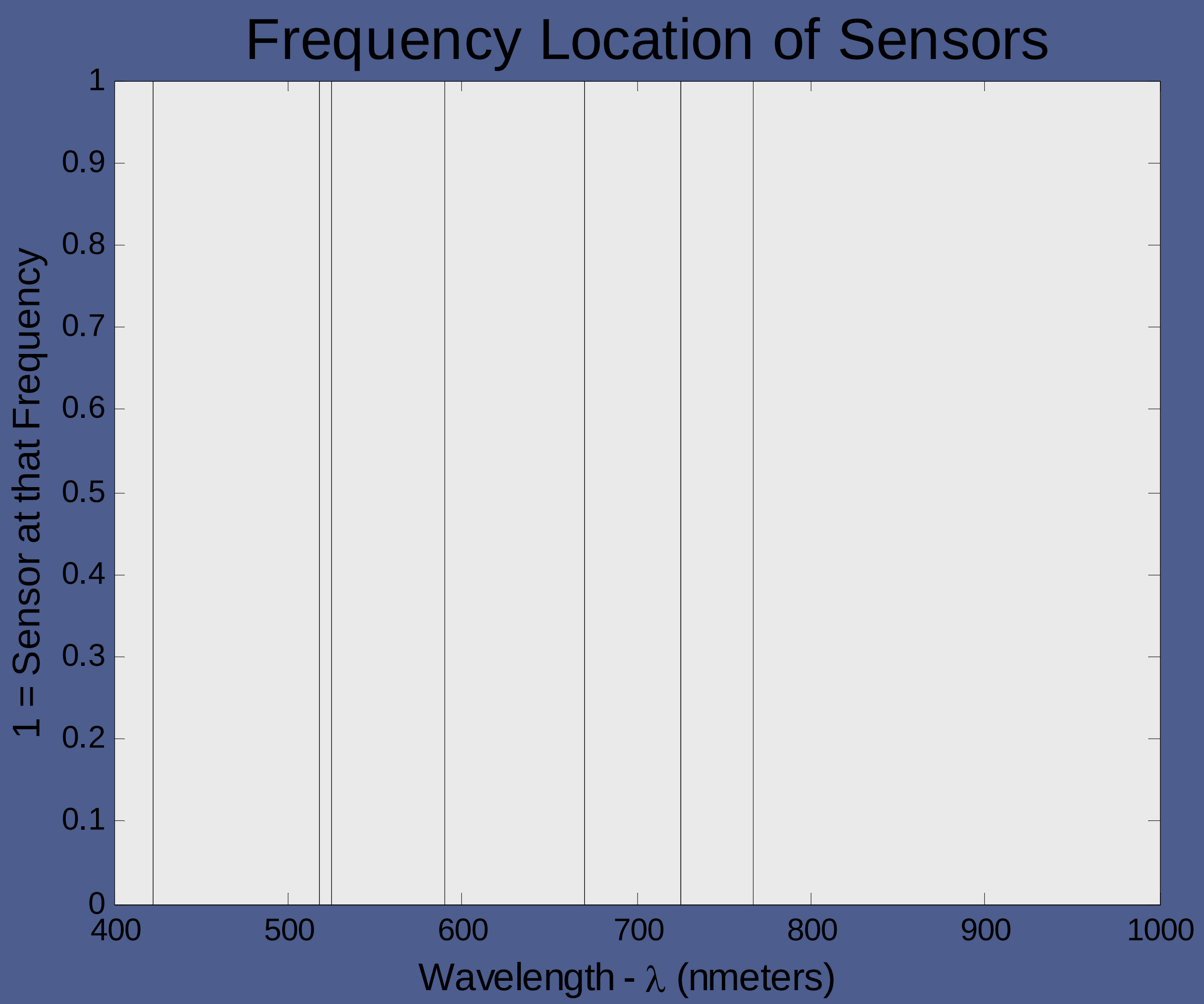
Large set with many similar images allows ensemble expectation required by Karhunen-Loeve


Sparsity
200
100
0
-100
-200
-300
-400
Eigen Value in dB
1
114
227
340
453
566
679
792
905
1018
1131
1244
1357
1470
1583
1696
1809
1922
2035
2148
2261
2374
2487
2600
2713
2826
2939
Eigen Vector Number



Sparsity
Eigen Value
12
10
8
6
4
2
0
1 4 7 10 13 16 19 22 25 28 31 34 37 40 43 46 49 52 55 58 61 64 67 70 73 76 79 82 85 88 91 94 97
Eigen Vector Number

Spectroscopic Application



Seven Line (Bandwidth~1.5Å) Filtered Detectors

Pseudo-random frequency selection meets incoherence requirement

The placement of these frequency sample points can be described by a Poisson statistical density with a “p” of 0.023 and a k=7.

The resulting placement is described by a random variable and is sufficiently incoherent to meet the requirements for compressive sensing.

Frequency sampling rate is below Nyquist criteria requirements

Double-Blind Biological Project

A double-blind distribution of samples containing complex organics and inorganic elements (Na, Li, K, Se, Cl, Urea, etc.) in sub-nL solutions were analyzed by Atomic Emission Spectroscopy

Signal reconstruction software unique to the frequency sample choices were implemented

RSD's of 0.975-0.997 were obtained in presence of complex organic matrices

Conclusions

Test sets of Images and spectroscopic data demonstrates the applicability of statically chosen pseudo-random vectors to represent the signal at significantly below the Nyquist sampling rate

Design validation tools have been and are continuing to be developed

DOD force protection and DHS Homeland security applications appear to be positively impact by this approach

General application of the techniques should address in part the data overload issues choking many current schenarios