New Basis

September 22, 2015

1 Preliminaries

Consider the basis defined by the function:

$$f_{i}(x) = \begin{cases} 1 & \text{if } x \leq i \\ 0 & \text{otherwise} \end{cases}$$
 (1.0.1)

That is, f_i is a left-hand step function. We define the inner product between two vectors as follows:

Definition 1.1.

$$\langle x, y \rangle = x^T y = \sum_i x_i y_i \tag{1.0.2}$$

where x_i, y_i are the components of the vectors x, y in the ith direction with respect to some basis vectors e_i .

We can define a matrix representation for the set of basis vectors f_i , by taking all inner products between all pairs basis vectors:

Definition 1.2.

$$F_{n,ij} = \langle f_i, f_j \rangle \tag{1.0.3}$$

This matrix has the representation:

$$F_{ij} = min(i,j) \tag{1.0.4}$$

An example of such a matrix is:

$$F_n = \begin{pmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 2 & 2 & 2 & 2 \\ 1 & 2 & 3 & 3 & 3 \\ 1 & 2 & 3 & 4 & 4 \\ 1 & 2 & 3 & 4 & 5 \end{pmatrix}$$
 (1.0.5)

This matrix is invertible.

Theorem 1.3.

$$det(F_n) = 1 (1.0.6)$$

Proof. Consider the matrix F^n . Subtract the n-1th column from the nth. We obtain a matrix with 0 on the final column except the entry $F_{(n,n)}^n = 1$. Since the top $(n-1) \times (n-1)$ is F^{n-1} we find that

$$det(F_n) = 1 \times det(F_{n-1}) \tag{1.0.7}$$

By recursion and $det(F_1) = 1$ we have $det(F_n) = 1$.

This matrix can be factorised as $F = LL^T$ where

$$L = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \dots 0 \\ 1 & 1 & 0 & 0 & 0 \dots 0 \\ 1 & 1 & 1 & 0 & 0 \dots 0 \\ \dots & & & & \\ 1 & 1 & 1 & 1 & 1 \dots 1 \end{pmatrix}$$
 (1.0.8)

From this it follows that

$$F^{-1} = \begin{pmatrix} 2 & -1 & 0 & 0 & 0 \dots 0 \\ -1 & 2 & -1 & 0 & 0 \dots 0 \\ 0 & -1 & 2 & -1 & 0 \dots 0 \\ \dots & & & & & \\ 0 & 0 & 0 & 0 \dots -1 & 1 \end{pmatrix}$$
(1.0.9)

Another matrix we will use a lot of is:

$$D = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \dots 0 \\ -1 & 1 & 0 & 0 & 0 \dots 0 \\ 0 & -1 & 0 & 0 & 0 \dots 0 \\ \dots & & & & & \\ 0 & 0 & 0 & 0 \dots -1 & 1 \end{pmatrix}$$
(1.0.10)

and by direct computation:

$$DL = I (1.0.11)$$

$\mathbf{2}$ Spectrum Sensing

We model our PSD signal q as a linear combination of the basis functions (1.0.1):

$$g\left(x\right) = \sum_{i} a_{i} f_{i} \tag{2.0.12}$$

To find the a_i , we correlate (take the inner product of) the signal against the basis (1.0.1).

Definition 2.1.

$$h_j = \langle g, f_j \rangle \tag{2.0.13}$$

$$= \sum_{i} g(x) f_{i}(x)$$
 (2.0.14)

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(2.0.14)
$$= \sum_{j} a_{i} f_{i}(x) f_{j}(x)$$

$$= a_i \langle f_i, f_i \rangle \tag{2.0.16}$$

$$\left(=\sum_{x=1}^{j}g\left(x\right)\right) \tag{2.0.17}$$

In matrix language $h = Fa^T$. This is the inner product between the signal g and the basis functions f_i .

Definition 2.2.

$$d_{i}(x) = \begin{cases} 1 & \text{if } x = i \\ -1 & \text{if } x = i - 1 \\ 0 & \text{otherwise} \end{cases}$$
 (2.0.18)

i.e. d_i is the i^{th} row of the matrix D.

$$D^T g = a (2.0.19)$$

Proof. From the definition of g (2.0.12)

$$D^T g = D^T \sum_i a_i f_i \tag{2.0.20}$$

$$=\sum_{i} a_i d_j^T f_i \tag{2.0.21}$$

$$= a\langle d_j, f_i \rangle \tag{2.0.22}$$

$$= a (2.0.23)$$

as

$$\langle d_j, f_i \rangle == \begin{cases} 1 & \text{if } i \leq j \\ 0 & \text{otherwise} \end{cases}$$
 (2.0.24)

This means

$$g = (D^T)^{-1} a = (D^{-1})^T a$$
 (2.0.25)

so using (1.0.11),

$$g = L^T a (2.0.26)$$

To recover \hat{a} , we minimise

$$||h - Fa||_2^2 (2.0.27)$$

in the noiseless case, and

$$||h_{\varepsilon} - Fa||_2^2 + \lambda ||a||_1 \tag{2.0.28}$$

in the noisy case, where

$$(h_{\varepsilon})_{i} = \langle (g + \varepsilon), f_{j} \rangle$$
 (2.0.29)

and $\varepsilon \sim \mathcal{N}(0, \sigma^2 I)$.

From \hat{a} we can recover \hat{g} from the following relation:

$$\hat{g} = L^T \hat{a} \tag{2.0.30}$$

3 Results

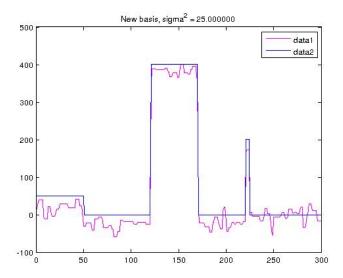


Figure 3.1:

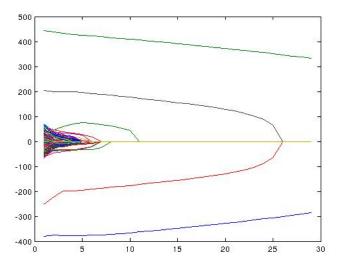


Figure 3.2:

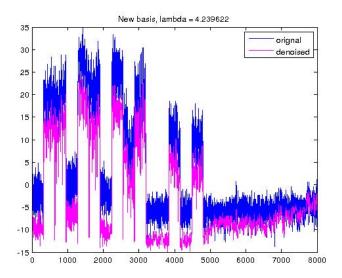


Figure 3.3:

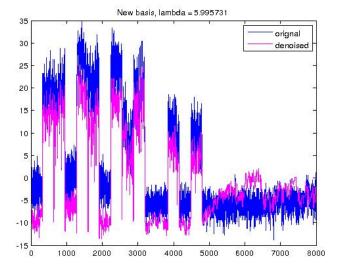


Figure 3.4:

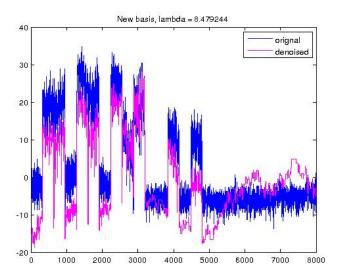


Figure 3.5:

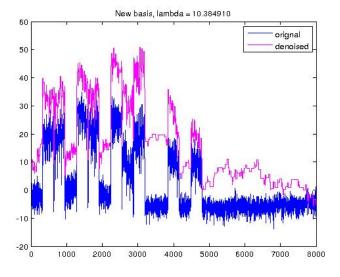


Figure 3.6:

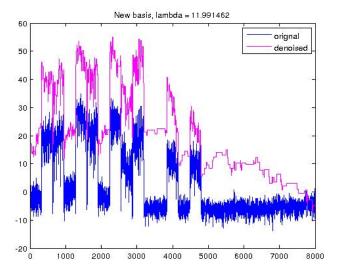


Figure 3.7: