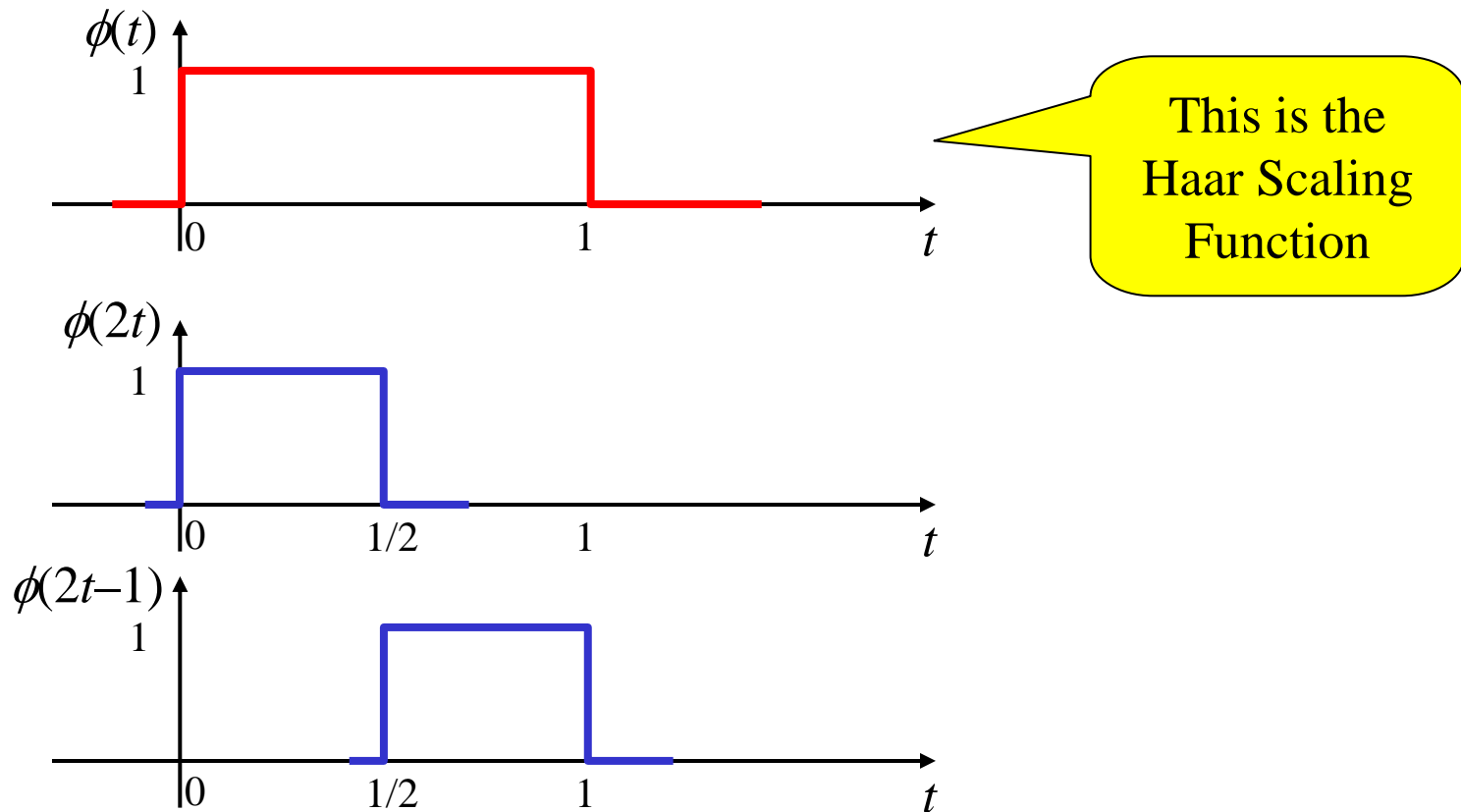


Wavelet Example: Haar Wavelet

Suppose we specify the MRE coefficients to be $h[n] = \left\{ \frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}} \right\}$

Then the MRE becomes $\phi(t) = \sum_n h(n) \sqrt{2} \phi(2t - n) \Rightarrow \phi(t) = \phi(2t) + \phi(2t - 1)$

Clearly the scaling function $\phi(t)$ as shown below satisfies this MRE

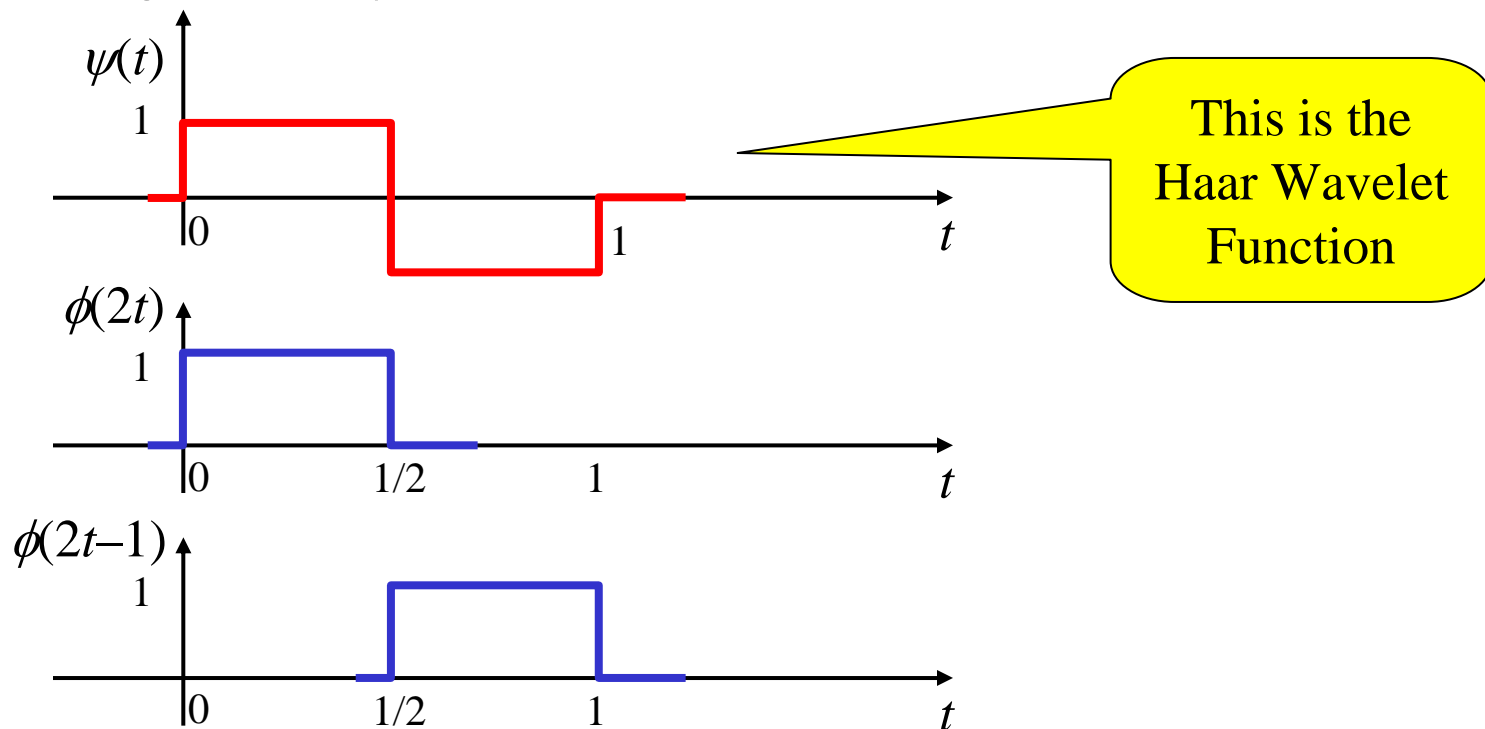


- Special case: finite number N of nonzero $h(n)$ and ON wavelets & scaling functions
- Given the $h(n)$ for the scaling function, then the $h_1(n)$ that define the wavelet function are given by $h_1[n] = (-1)^n h(N - 1 - n)$ where N is the length of the filter

Thus the WE coefficients are $h_1[n] = \left\{ \frac{1}{\sqrt{2}}, -\frac{1}{\sqrt{2}} \right\}$

Then the WE becomes $\psi(t) = \sum_n h_1(n) \sqrt{2} \phi(2t - n) \Rightarrow \psi(t) = \phi(2t) - \phi(2t - 1)$

Clearly the scaling function $\phi(t)$ as shown below satisfies this MRE



Define a nested set of signal spaces

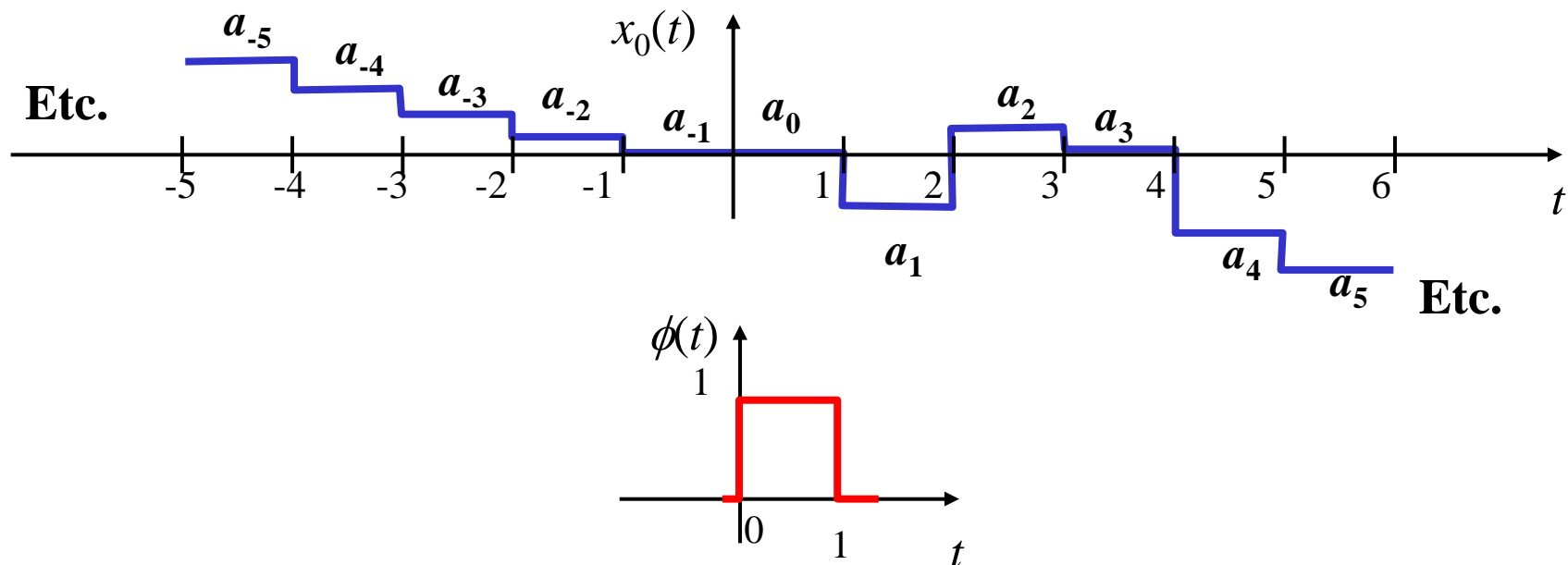
$$\cdots \subset V_{-2} \subset V_{-1} \subset V_0 \subset V_1 \subset V_2 \subset \cdots \subset L^2$$

Let V_0 be the space spanned by the integer translations of scaling function $\phi(t)$ so that **if** $x_0(t)$ is in V_0 **then** it can be represented by:

$$x_0(t) = \sum_k a_k \phi(t - k)$$

Q: For the Haar scaling function what kind of functions are in V_0 ??

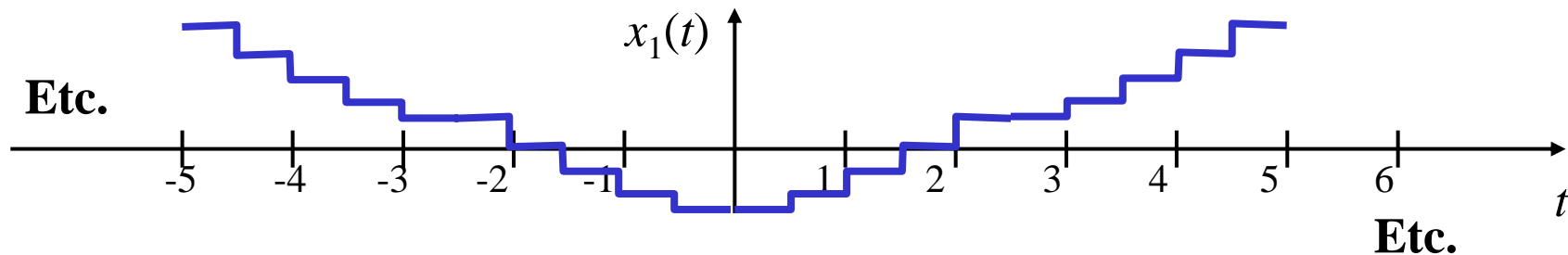
A: Those that are “piece-wise” constant on the intervals $[k, k+1]$ for integer k ...



If we let V_1 be the space spanned by integer translates of $\phi(2t)$ then V_1 is indeed a space of functions having higher resolution.

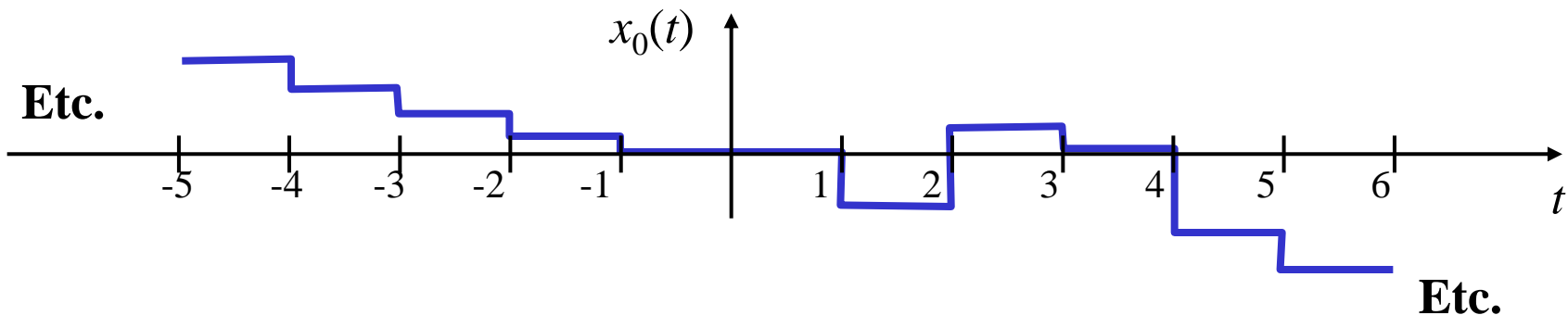
Q: For the Haar scaling function what kind of functions are in V_1 ??

A: Those that are “piece-wise” constant on the intervals $[k/2, k/2 + 1/2]$ for integer k

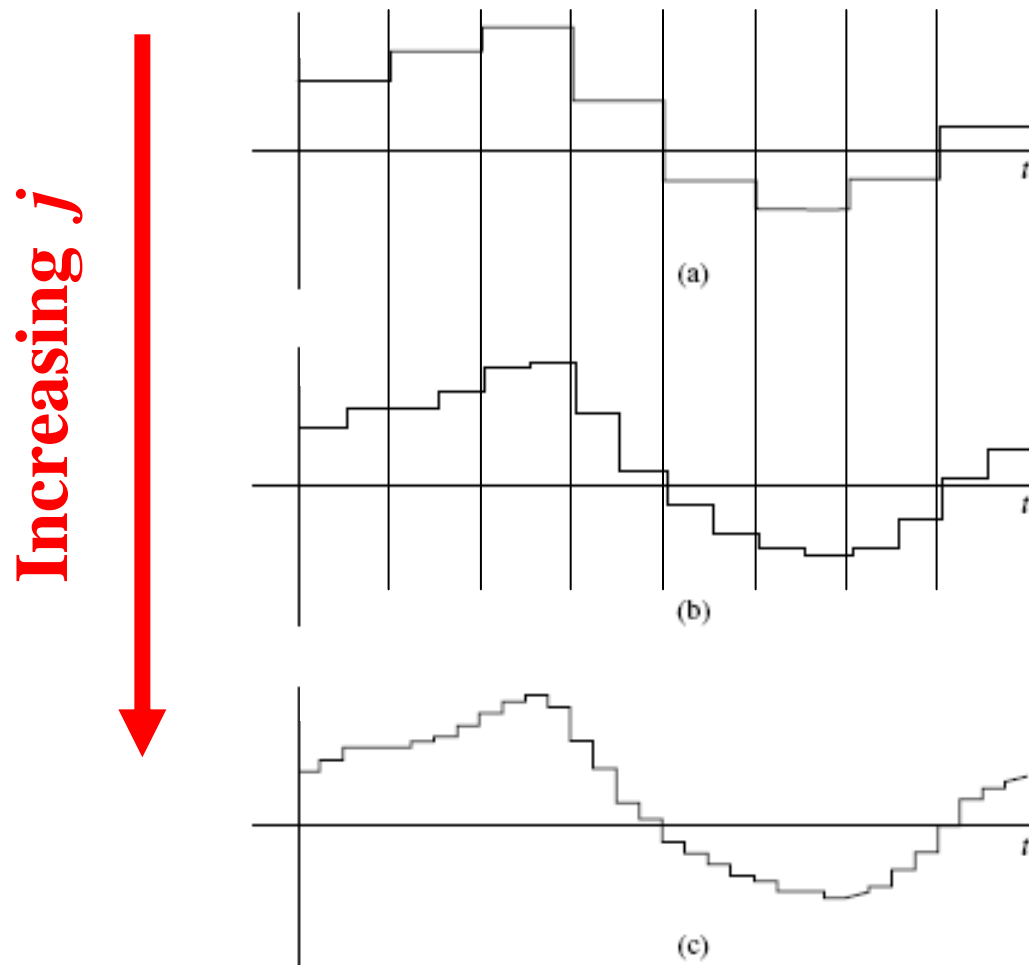


Note: $x_0(t)$ is also in V_1 because it is also “piece-wise” constant on $[k/2, k/2 + 1/2]$

In fact, $x_0(t)$ is also in every V_j for $j \geq 0 \dots$ that is the nesting!!!



If we keep going to higher j values we get finer and finer resolution and can ultimately express (in the limit of j) any finite energy signal

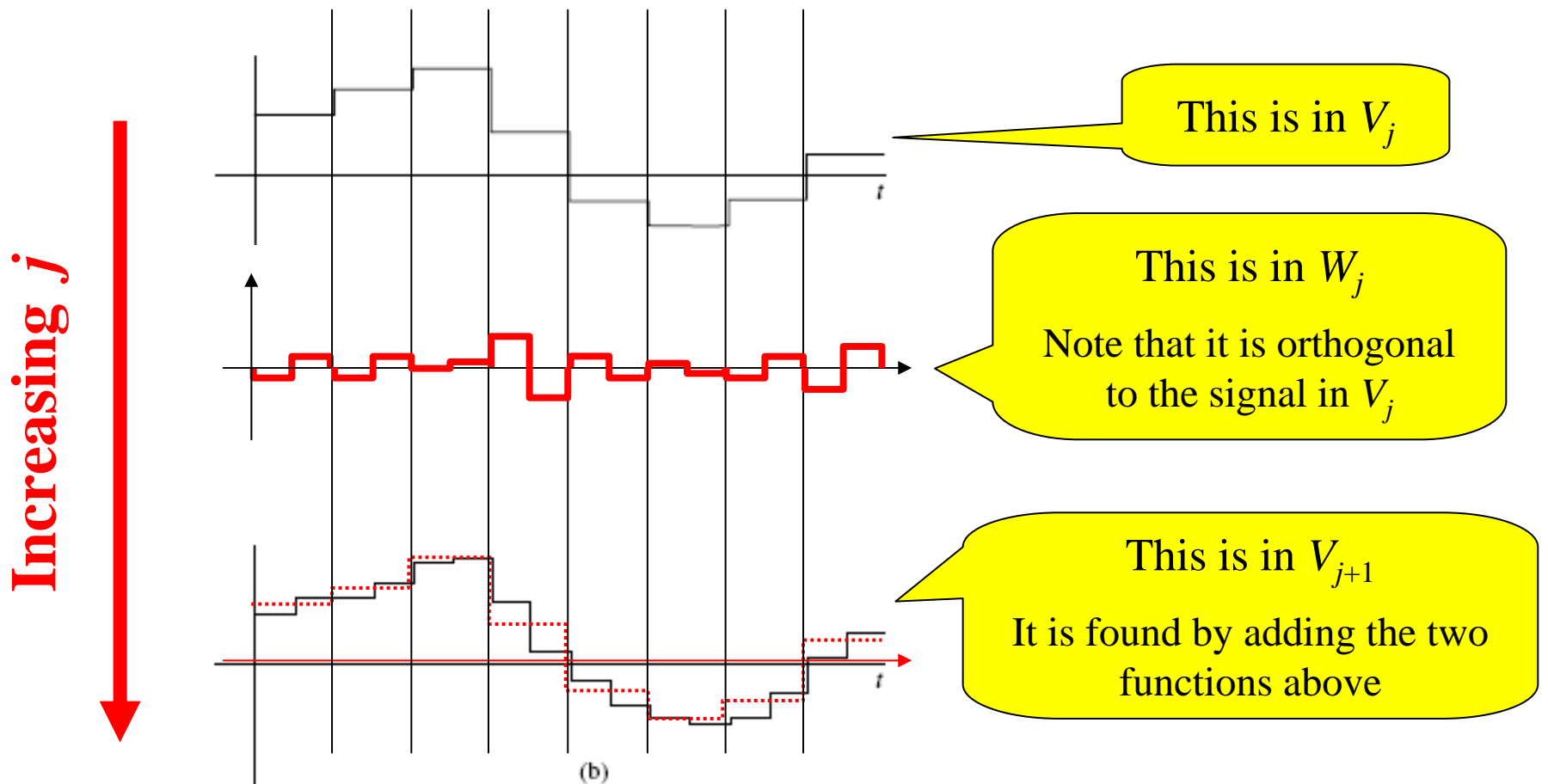


This MRA development started at V_0 and worked its way up to higher resolutions...

Figure 15.8 from Textbook

How do the wavelets enter into this?

- To go from V_j to higher resolution V_{j+1} requires the addition of “details”
 - These details are the part of V_{j+1} not able to be represented in V_j
 - This is captured through W_j the “orthogonal complement” of V_j w.r.t V_{j+1}



EE269

Signal Processing for Machine Learning

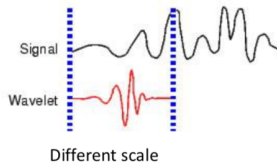
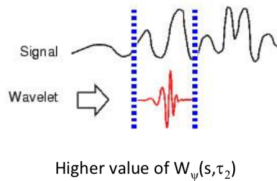
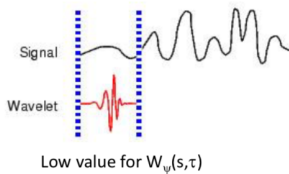
Lecture 17

Instructor : Mert Pilanci

Stanford University

March 13, 2019

Wavelets



Discrete Wavelet Transform

- ▶ Discrete shifts and scales $\psi(\frac{t-\tau}{s})$
- ▶ Suppose we have a signal of length N

$$x = [x_1, x_2, \dots, x_N]$$

- ▶ Consider a length $N/2$ approximation of x , e.g., for transmission

Discrete Wavelet Transform

- ▶ Discrete shifts and scales $\psi(\frac{t-\tau}{s})$
- ▶ Suppose we have a signal of length N

$$x = [x_1, x_2, \dots, x_N]$$

- ▶ Consider a length $N/2$ approximation of x , e.g., for transmission
- ▶ pairwise averages:

$$x_k = \frac{x_{2k-1} + x_{2k}}{2}, \quad k = 1, \dots, N/2$$

Discrete Wavelet Transform

- ▶ Discrete shifts and scales $\psi(\frac{t-\tau}{s})$
- ▶ Suppose we have a signal of length N

$$x = [x_1, x_2, \dots, x_N]$$

- ▶ Consider a length $N/2$ approximation of x , e.g., for transmission
- ▶ pairwise averages:

$$x_k = \frac{x_{2k-1} + x_{2k}}{2}, \quad k = 1, \dots, N/2$$

- ▶ example

$$x = [6, 12, 15, 15, 14, 12, 120, 116] \rightarrow s = [9, 15, 13, 118]$$

- ▶ suppose that we are allowed to send $N/2$ more numbers
- ▶ differences

$$d_k = \frac{x_{2k-1} - x_{2k}}{2}, \quad k = 1, \dots, N/2$$

- ▶ we can recover x

$$x = [6, 12, 15, 15, 14, 12, 120, 116] \rightarrow$$
$$[s \mid d] = [9, 15, 13, 118 \mid 3, 0, -1, -2]$$

- ▶ suppose that we are allowed to send $N/2$ more numbers
- ▶ differences

$$d_k = \frac{x_{2k-1} - x_{2k}}{2}, \quad k = 1, \dots, N/2$$

- ▶ we can recover x

$$x = [6, 12, 15, 15, 14, 12, 120, 116] \rightarrow$$
$$[s \mid d] = [9, 15, 13, 118 \mid 3, 0, -1, -2]$$

- ▶ One step Haar Transformation $x \rightarrow [s \mid d]$

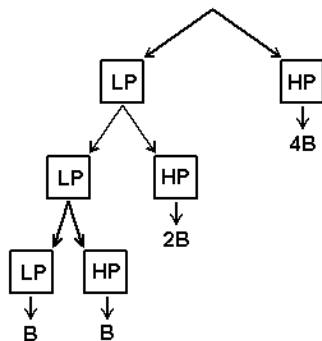
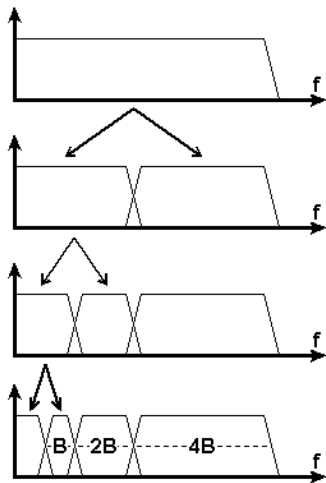
One Step Haar Transformation

$$\begin{bmatrix}
 \frac{1}{2} & \frac{1}{2} & 0 & 0 & 0 & 0 & 0 & 0 \\
 0 & 0 & \frac{1}{2} & \frac{1}{2} & 0 & 0 & 0 & 0 \\
 0 & 0 & 0 & 0 & \frac{1}{2} & \frac{1}{2} & 0 & 0 \\
 0 & 0 & 0 & 0 & 0 & 0 & \frac{1}{2} & \frac{1}{2} \\
 \hline
 -\frac{1}{2} & \frac{1}{2} & 0 & 0 & 0 & 0 & 0 & 0 \\
 0 & 0 & -\frac{1}{2} & \frac{1}{2} & 0 & 0 & 0 & 0 \\
 0 & 0 & 0 & 0 & -\frac{1}{2} & \frac{1}{2} & 0 & 0 \\
 0 & 0 & 0 & 0 & 0 & 0 & -\frac{1}{2} & \frac{1}{2}
 \end{bmatrix} \cdot \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \\ x_8 \end{bmatrix} = \frac{1}{2} \begin{bmatrix} x_1 + x_2 \\ x_3 + x_4 \\ x_5 + x_6 \\ x_7 + x_8 \\ \hline x_2 - x_1 \\ x_4 - x_3 \\ x_6 - x_5 \\ x_8 - x_7 \end{bmatrix}$$

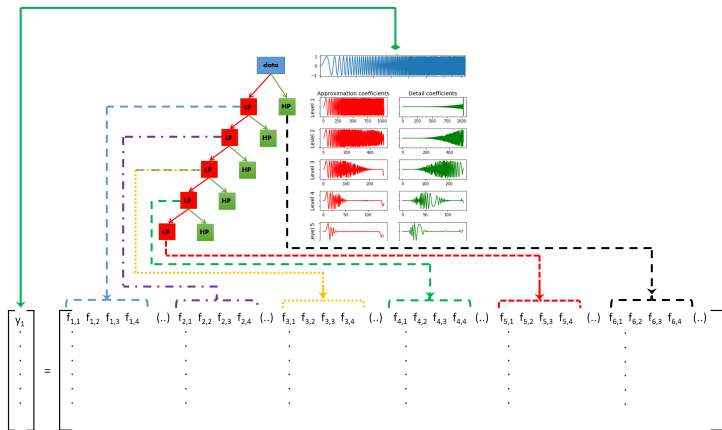
Discrete Haar Transform Matrix

- ▶ repeat the computation on the **means**
- ▶ keep differences in each step

Discrete Haar Wavelet Transform

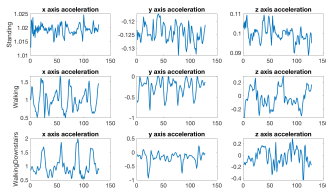


Wavelet Transform Features

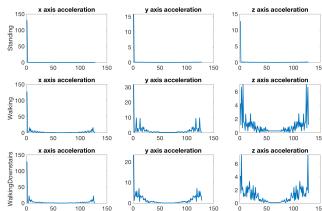


- ▶ mean, median
- ▶ variance
- ▶ zero crossing rate, mean crossing rate
- ▶ entropy

Results: training set: 7724 signals, test set: 2575 signals



3-Nearest Neighbors, ℓ_2 -norm distance on $x[n]$. **Accuracy : 0.77**

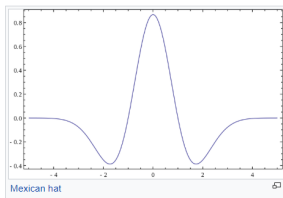
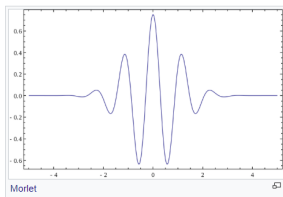
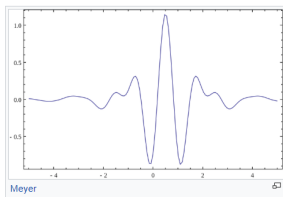


3-Nearest Neighbors, ℓ_2 -norm distance on $|X[k]|$. **Accuracy : 0.85**

Human Activity Recognition dataset

- ▶ 3-Nearest Neighbors, ℓ_2 -norm distance on $x[n]$.
accuracy : 77%
- ▶ 3-Nearest Neighbors, ℓ_2 -norm distance on $|X[k]|$.
accuracy : 85%
- ▶ 1D Convolutional Net (4 layers)
accuracy : 91%
- ▶ Wavelet Transform Features (entropy, zero crossing, simple statistics) + linear classifier
accuracy : 95%

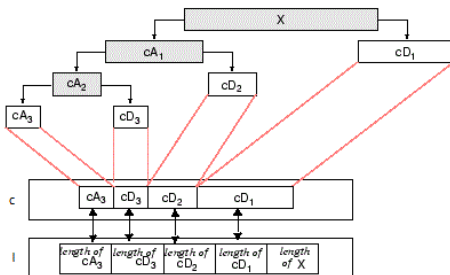
Other Wavelets



Other Wavelets

► In MATLAB

$[c,l] = \text{wavedec}(x,n,\text{wname})$ returns the wavelet decomposition of the signal x at level n using the wavelet wname



What makes a good wavelet

Application specific

- ▶ Compact time support vs frequency support
- ▶ Smoothness
- ▶ Orthogonality