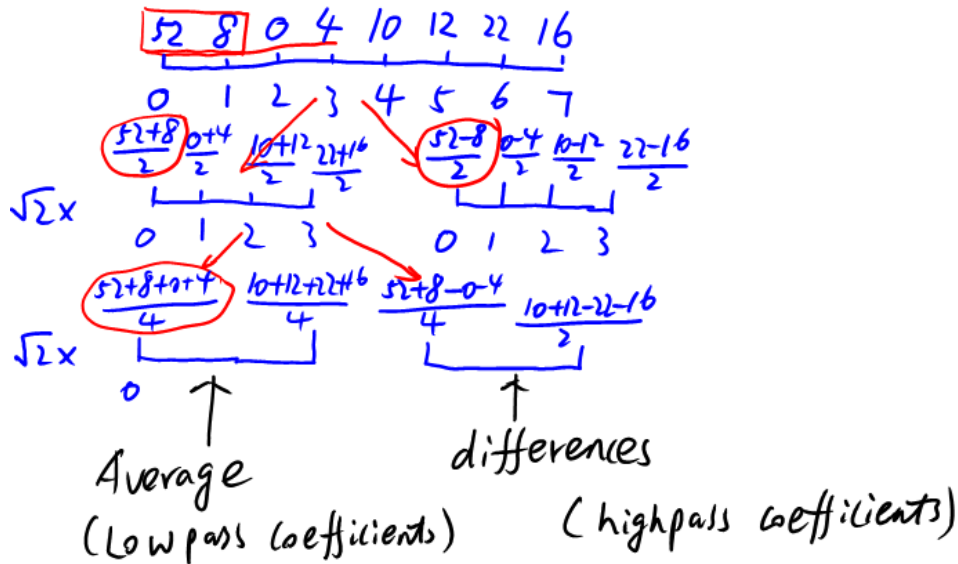


3. DWT (Discrete Wavelet or Framelet Transform)

August-14-08
12:58 PM1. DWT using the Haar Filter. $[\frac{1}{2} \frac{1}{2}]$ and $[\frac{1}{2} -\frac{1}{2}]$ 

2. Some notations

1. $u = \{u_k\}_{k=-\infty}^{\infty} : \mathbb{Z} \rightarrow \mathbb{C}$ is a sequence on $\mathbb{Z}$.
2. Its Fourier series $\hat{u}$ is denoted by

$$\hat{u}(\xi) := \sum_{k=-\infty}^{\infty} u_k e^{-ik\xi}, \quad \xi \in \mathbb{R}.$$

- 3 A **FIR** (finite impulse filter) u (or $\hat{u}$) is a finitely supported sequence on $\mathbb{Z}$.

4. Convolution of u and v :

$$[u * v]_j := \sum_{k=-\infty}^{\infty} u_{j-k} v_k. \quad \text{That is, } \widehat{u * v}(\xi) = \hat{u}(\xi) \hat{v}(\xi).$$

- 5 $\bar{x}$ denotes the complex conjugate of $x \in \mathbb{C}$.

6. The sequence W given by $\widehat{W}(\xi) := \overline{\widehat{U}(\xi)} \widehat{V}(\xi)$ is

$$W_j = \sum_{k=-\infty}^{\infty} \overline{U_k} V_{j+k}, \quad j \in \mathbb{Z}.$$

7. For $f \in L_1(\mathbb{R})$, its Fourier transform is defined to be

$$\widehat{f}(\xi) := \int_{\mathbb{R}} f(t) e^{-it\xi} dt, \quad \xi \in \mathbb{R}.$$

8. Convolution of $f, g \in L_1(\mathbb{R})$:

$$f * g(\xi) := \int_{\mathbb{R}} f(\xi - t) g(t) dt, \quad \xi \in \mathbb{R}.$$

$$\text{That is, } \widehat{f * g}(\xi) = \widehat{f}(\xi) \widehat{g}(\xi).$$

3. Perfect Reconstruction Wavelet Filters:

primal: lowpass a , highpass $b^1, \dots, b^L$

Dual: lowpass $\tilde{a}$, highpass $\tilde{b}^1, \dots, \tilde{b}^L$.

Perfect Reconstruction Condition (in the frequency domain):

$$\begin{bmatrix} \widehat{\tilde{a}}(\xi) & \widehat{\tilde{b}^1}(\xi) & \dots & \widehat{\tilde{b}^L}(\xi) \\ \widehat{\tilde{a}}(\xi + \pi) & \widehat{\tilde{b}^1}(\xi + \pi) & \dots & \widehat{\tilde{b}^L}(\xi + \pi) \end{bmatrix} \begin{bmatrix} \widehat{a}(\xi) & \widehat{a}(\xi + \pi) \\ \widehat{b^1}(\xi) & \widehat{b^1}(\xi + \pi) \\ \vdots & \vdots \\ \widehat{b^L}(\xi) & \widehat{b^L}(\xi + \pi) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}.$$

That is,

$$\begin{cases} \widehat{\tilde{a}}(\xi) \widehat{a}(\xi) + \sum_{l=1}^L \widehat{\tilde{b}^l}(\xi) \widehat{b^l}(\xi) = 1 \\ \widehat{\tilde{a}}(\xi) \widehat{a}(\xi + \pi) + \sum_{l=1}^L \widehat{\tilde{b}^l}(\xi) \widehat{b^l}(\xi + \pi) = 0 \end{cases} \quad \forall \xi \in \mathbb{R}$$

In the time domain, this condition is equivalent to:

$$\begin{cases} \sum_{k=-\infty}^{\infty} \overline{a_{j+k}} a_k + \sum_{l=1}^L \sum_{k=-\infty}^{\infty} \overline{b_{j+k}^l} b_k^l = \delta_j \quad \forall j \in \mathbb{Z}, \\ \sum_{k=-\infty}^{\infty} \overline{a_{j+k}} (-1)^k a_k + \sum_{l=1}^L \sum_{k=-\infty}^{\infty} \overline{b_{j+k}^l} (-1)^k b_k^l = 0, \end{cases}$$

Where δ denotes the **Dirac sequence** such that

$$\delta_0 = 1 \quad \text{and} \quad \delta_j = 0 \quad \forall j \neq 0.$$

This is also equivalent to

$$\begin{cases} \sum_{k=-\infty}^{\infty} \overline{a_{j+2k}} a_{2k} + \sum_{l=1}^L \sum_{k=-\infty}^{\infty} \overline{b_{j+2k}^l} b_{2k}^l = \frac{1}{2} \delta_j \quad \forall j \in \mathbb{Z}, \\ \sum_{k=-\infty}^{\infty} \overline{a_{j+2k+1}} a_{2k+1} + \sum_{l=1}^L \sum_{k=-\infty}^{\infty} \overline{b_{j+2k+1}^l} b_{2k+1}^l = \frac{1}{2} \delta_j \end{cases}$$

- 4 The special case $L=1$: one lowpass and one highpass
The perfect reconstruction condition becomes

$$\begin{bmatrix} \widehat{\overline{a}}(\xi) & \widehat{\overline{b}}(\xi) \\ \widehat{\overline{a}}(\xi+\pi) & \widehat{\overline{b}}(\xi+\pi) \end{bmatrix} \begin{bmatrix} \widehat{a}(\xi) & \widehat{a}(\xi+\pi) \\ \widehat{b}(\xi) & \widehat{b}(\xi+\pi) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}.$$

This is equivalent to (noting that they are square matrices)

$$\begin{bmatrix} \widehat{a}(\xi) & \widehat{a}(\xi+\pi) \\ \widehat{b}(\xi) & \widehat{b}(\xi+\pi) \end{bmatrix} \begin{bmatrix} \widehat{\overline{a}}(\xi) & \widehat{\overline{b}}(\xi) \\ \widehat{\overline{a}}(\xi+\pi) & \widehat{\overline{b}}(\xi+\pi) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}.$$

That is

$$I. \quad \boxed{\widehat{a}(\xi) \widehat{a}(\xi) + \widehat{a}(\xi+\pi) \widehat{a}(\xi+\pi) = 1} \quad (*)$$

$$II. \quad \begin{cases} \widehat{a}(\xi) \widehat{b}(\xi) + \widehat{a}(\xi+\pi) \widehat{b}(\xi+\pi) = 0 \\ \overline{\widehat{a}(\xi)} \widehat{b}(\xi) + \overline{\widehat{a}(\xi+\pi)} \widehat{b}(\xi+\pi) = 0 \end{cases}$$

$$III. \quad \overline{\widehat{b}(\xi)} \widehat{b}(\xi) + \overline{\widehat{b}(\xi+\pi)} \widehat{b}(\xi+\pi) = 0$$

In the time domain, this is equivalent to

$$\text{Fundamental} \quad \boxed{\sum_{k=-\infty}^{\infty} \overline{a_{2j+k}} \tilde{a}_k = \frac{1}{2} \delta_j \quad (a \text{ and } \tilde{a} \text{ are biorthogonal})} \quad (*)$$

$$\sum_{k=-\infty}^{\infty} \overline{a_{2j+k}} \tilde{b}_k = 0 \quad (a \text{ and } \tilde{b} \text{ are orthogonal})$$

$$\sum_{k=-\infty}^{\infty} \overline{\tilde{a}_{2j+k}} b_k = 0 \quad (\tilde{a} \text{ and } b \text{ are orthogonal})$$

$$\sum_{k=-\infty}^{\infty} \overline{b_{2j+k}} \tilde{b}_k = \frac{1}{2} \delta_j \quad (b \text{ and } \tilde{b} \text{ are biorthogonal})$$

If the biorthogonal condition in (*) (that is, a and $\tilde{a}$ are biorthogonal), a standard choice to design the highpass filters b and $\tilde{b}$ is

$$\begin{aligned} \widehat{b}(\xi) &:= e^{-i\xi} \overline{\widehat{a}(\xi+\pi)}, & b_k &= (-1)^k \overline{\tilde{a}_{1-k}} \\ \widehat{\tilde{b}}(\xi) &:= e^{-i\xi} \widehat{a}(\xi+\pi), & \tilde{b}_k &= (-1)^k \tilde{a}_{1-k} \end{aligned}$$

Since it is easy to check that $\widehat{a}(\xi) \widehat{a}(\xi) + \widehat{a}(\xi+\pi) \widehat{a}(\xi+\pi) = 1$

$$\begin{aligned}
& \begin{bmatrix} \widehat{a}(\xi) & \widehat{a}(\xi+\pi) \\ \widehat{b}(\xi) & \widehat{b}(\xi+\pi) \end{bmatrix} \begin{bmatrix} \overline{\widehat{a}(\xi)} & \overline{\widehat{a}(\xi+\pi)} \\ \overline{\widehat{b}(\xi)} & \overline{\widehat{b}(\xi+\pi)} \end{bmatrix} \\
&= \begin{bmatrix} \widehat{a}(\xi) & \widehat{a}(\xi+\pi) \\ e^{i\xi} \widehat{a}(\xi+\pi) & -e^{i\xi} \widehat{a}(\xi) \end{bmatrix} \begin{bmatrix} \widehat{a}(\xi) & e^{-i\xi} \overline{\widehat{a}(\xi+\pi)} \\ \widehat{a}(\xi+\pi) & -e^{i\xi} \overline{\widehat{a}(\xi)} \end{bmatrix} \\
&= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}.
\end{aligned}$$

Definition: a is biorthogonal (or dual) to $\tilde{a}$ (or $\tilde{a}$ is a dual mask/filter to a) if

$$\widehat{\tilde{a}}(\xi) \widehat{a}(\xi) + \widehat{\tilde{a}}(\xi+\pi) \widehat{a}(\xi+\pi) = 1.$$

In particular, if a is a dual mask of itself, then we call a is an **orthogonal mask/filter**. That is,

$$|\widehat{a}(\xi)|^2 + |\widehat{a}(\xi+\pi)|^2 = 1.$$

Example. The Haar filter a : $\begin{array}{cc} \frac{1}{2} & \frac{1}{2} \\ 0 & 1 \end{array}$. So

$$\widehat{a}(\xi) = \frac{1+e^{-i\xi}}{2} \Rightarrow |\widehat{a}(\xi)|^2 = \cos^2(\xi/2).$$

$$\Rightarrow |\widehat{a}(\xi)|^2 + |\widehat{a}(\xi+\pi)|^2 = \cos^2(\xi/2) + \sin^2(\xi/2) = 1.$$

Conclusion: The Haar filter is orthogonal. The highpass filter

$$\widehat{b}(\xi) = e^{-i\xi} \overline{\widehat{a}(\xi+\pi)} = \frac{1}{2}(e^{-i\xi} - 1)$$

$$\text{so } b: \begin{array}{cc} -\frac{1}{2} & \frac{1}{2} \\ 0 & 1 \end{array}$$

5 The transition operator and the subdivision operator

Let u and v be two sequences on $\mathbb{Z}$.

The transition operator $T_{u,2}$ is defined to be

$$[T_{u,2} v]_j := \sum_{k=-\infty}^{\infty} v_k \overline{u_{k-2j}}, \quad j \in \mathbb{Z}.$$

The subdivision operator $S_{u,2}$ is defined to be

$$[S_{u,2} v]_j := 2 \sum_{k=-\infty}^{\infty} v_k u_{j-2k}, \quad j \in \mathbb{Z}.$$

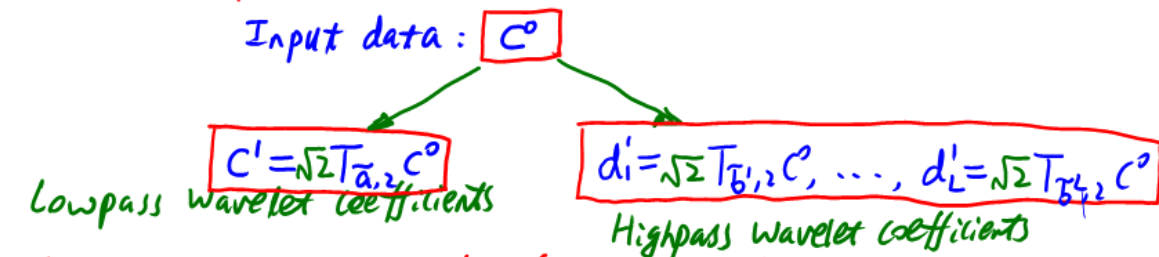
In the frequency domain, we have

$$\widehat{T_{u,2} v}(\xi) = \frac{1}{2} [\widehat{v}(\xi) \overline{\widehat{u}(\xi)} + \widehat{v}(\xi+\pi) \overline{\widehat{u}(\xi+\pi)}]$$

$$\widehat{S_{u,2} v}(\xi) = 2 \widehat{v}(2\xi) \widehat{u}(\xi).$$

6 The Discrete Wavelet/Framelet Transform:

The Decomposition Transform (or Algorithm):



The Reconstruction Transform (or Algorithm)

$$\hat{c}^0 := \frac{1}{\sqrt{2}} S_{a,2} c^1 + \frac{1}{\sqrt{2}} \sum_{\ell=1}^L S_{b^{\ell},2} d_{\ell}^1$$

Theorem (Perfect Reconstruction): $\hat{c}^0 = c^0$. That is,

$$c^0 = S_{a,2} T_{\bar{a},2} c^0 + \sum_{\ell=1}^L S_{b^{\ell},2} T_{\bar{b}^{\ell},2} c^0 \quad \forall \text{ sequences } c^0$$

if and only if

$$\begin{bmatrix} \widehat{\hat{a}}(\xi) & \widehat{\hat{b}^1}(\xi) & \dots & \widehat{\hat{b}^L}(\xi) \\ \widehat{\hat{a}}(\xi+\pi) & \widehat{\hat{b}^1}(\xi+\pi) & \dots & \widehat{\hat{b}^L}(\xi+\pi) \end{bmatrix} \begin{bmatrix} \hat{a}(\xi) & \hat{a}(\xi+\pi) \\ \hat{b}^1(\xi) & \hat{b}^1(\xi+\pi) \\ \vdots & \vdots \\ \hat{b}^L(\xi) & \hat{b}^L(\xi+\pi) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}.$$

Proof. Note that

$$\begin{aligned} \widehat{S_{a,2} T_{\bar{a},2} c^0}(\xi) &= 2 \widehat{T_{\bar{a},2} c^0}(2\xi) \hat{a}(\xi) \\ &= \widehat{c^0}(\xi) \widehat{\hat{a}}(\xi) \hat{a}(\xi) + \widehat{c^0}(\xi+\pi) \widehat{\hat{a}}(\xi+\pi) \hat{a}(\xi) \end{aligned}$$

$$\text{and } \widehat{S_{b^{\ell},2} T_{\bar{b}^{\ell},2} c^0}(\xi) = \widehat{c^0}(\xi) \widehat{\hat{b}^{\ell}}(\xi) \hat{b}^{\ell}(\xi) + \widehat{c^0}(\xi+\pi) \widehat{\hat{b}^{\ell}}(\xi+\pi) \hat{b}^{\ell}(\xi)$$

Consequently,

$$\begin{aligned} \widehat{S_{a,2} T_{\bar{a},2} c^0}(\xi) + \sum_{\ell=1}^L \widehat{S_{b^{\ell},2} T_{\bar{b}^{\ell},2} c^0}(\xi) \\ = \widehat{c^0}(\xi) \left[\widehat{\hat{a}}(\xi) \hat{a}(\xi) + \sum_{\ell=1}^L \widehat{\hat{b}^{\ell}}(\xi) \hat{b}^{\ell}(\xi) \right] \\ + \widehat{c^0}(\xi+\pi) \left[\widehat{\hat{a}}(\xi+\pi) \hat{a}(\xi) + \sum_{\ell=1}^L \widehat{\hat{b}^{\ell}}(\xi+\pi) \hat{b}^{\ell}(\xi) \right] \end{aligned}$$

Therefore, the perfect reconstruction property is equivalent to

$$\widehat{\hat{a}}(\xi) \hat{a}(\xi) + \sum_{\ell=1}^L \widehat{\hat{b}^{\ell}}(\xi) \hat{b}^{\ell}(\xi) = 1$$

$$\text{and } \widehat{\hat{a}}(\xi+\pi) \hat{a}(\xi) + \sum_{\ell=1}^L \widehat{\hat{b}^{\ell}}(\xi+\pi) \hat{b}^{\ell}(\xi) = 0.$$

This completes the proof. $\square$

7 Multilevel Discrete Wavelet/Framelet Transform.

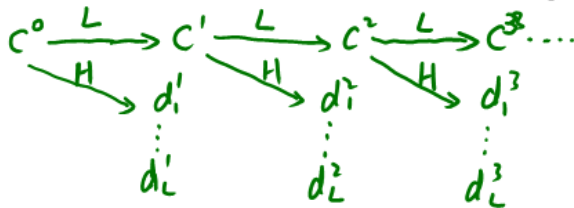
We can perform DWT on the lowpass wavelet coefficients again and again:

$$C^{\wedge} := \sqrt{2} T_{\alpha,2} C^{\wedge-1}$$

and

$$d_1^{\wedge} := \sqrt{2} T_{\beta^1,2} C^{\wedge-1}, \dots, d_L^{\wedge} := \sqrt{2} T_{\beta^L,2} C^{\wedge-1}.$$

That is, we have the following diagram:



8 Implementation of $T_{u,2}$ and $S_{u,2}$

$$\begin{aligned} * [T_{u,2} V]_j &= \sum_{k=-\infty}^{\infty} V_k \overline{u_{k-2j}} = \sum_{k=-\infty}^{\infty} V_k \overline{u_{-(2j-k)}} = \sum_{k=-\infty}^{\infty} V_k \overline{u_{2j-k}} \\ &= (V * u^*)_{2j}, \text{ where } u_k^* = \overline{u_{-k}} \end{aligned}$$

That is, $\widehat{u^*}(\xi) = \overline{\widehat{u}(\xi)}$. Hence

$$V \xrightarrow{T_{u,2}} T_{u,2} V \equiv V * u^* \xrightarrow[\text{by } 2]{\text{down sampling}} (V * u^*) \downarrow_2,$$

where down sampling by 2 is $(V \downarrow_2)_j = V_{2j}$

Note that the support of $(V \downarrow_2)$ is just half of V .

$$\begin{aligned} * [S_{u,2} V]_j &= 2 \sum_{k=-\infty}^{\infty} V_k u_{j-2k} = 2 \sum_{k=-\infty}^{\infty} (V \uparrow_2)_{2k} u_{j-2k} \\ &= 2 (V \uparrow_2 * u)_j, \end{aligned}$$

where the up sampling by 2 is

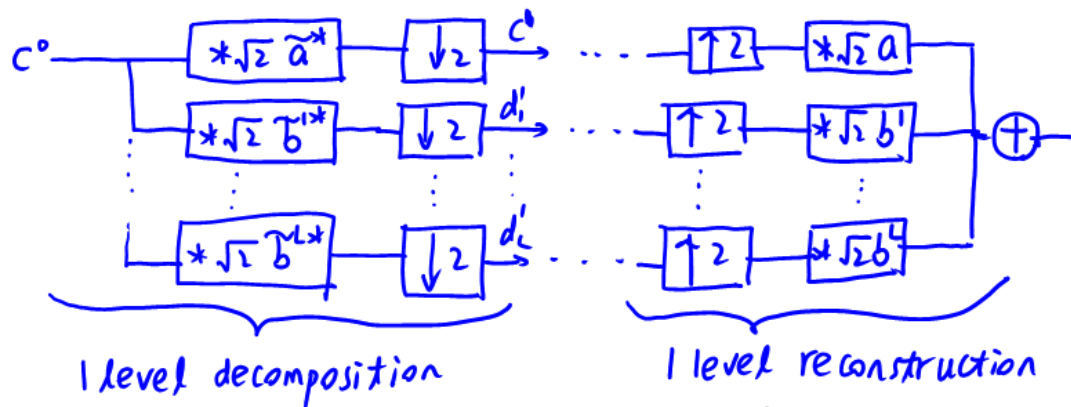
$$(V \uparrow_2)_k = \begin{cases} V_{k/2}, & \text{if } k \text{ is even} \\ 0, & \text{if } k \text{ is odd} \end{cases}$$

ex. $\begin{array}{ccccccccc} 9 & -4 & 5 & -3 & 8 & & & & \\ | & | & | & | & | & | & | & | & | \\ -2 & -1 & 0 & 1 & 2 & & & & \end{array} \xrightarrow[\text{by } 2]{\text{up sampling}} \begin{array}{ccccccccccccc} 9 & 0 & -4 & 0 & 5 & 0 & -3 & 0 & 8 & & & & \\ | & | & | & | & | & | & | & | & | & | & | & | & | \\ -4 & -3 & -2 & -1 & 0 & 1 & 2 & 3 & 4 & & & & \end{array}$

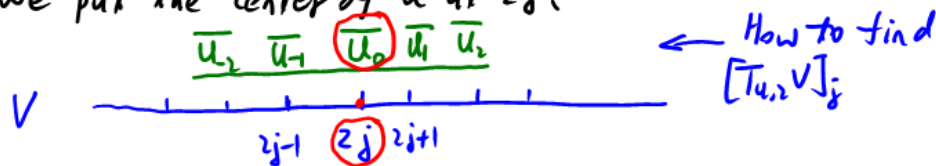
Therefore

$$V \xrightarrow{S_{u,2}} S_{u,2} V \equiv V \xrightarrow[\text{by } 2]{\text{up sampling}} V \uparrow_2 \xrightarrow{*u} (V \uparrow_2) * u \xrightarrow{\times 2} 2(V \uparrow_2) * u$$

So the Discrete Wavelet Transform can be also viewed as



* More intuitively, to calculate $[T_{u,2} V]_j = \sum_{k=-\infty}^{\infty} V_k \overline{u_{k-2j}}$, we put the center of u at $2j$:



Note: No flipping of the filter u , but change u into $\overline{u}$!

Caution: There are several normalization conditions on the lowpass filter a and $\tilde{a}$. Here we are using

$$\hat{a}(0) = \hat{\tilde{a}}(0) = 1. \text{ That is, } \sum_{k=-\infty}^{\infty} a_k = \sum_{k=-\infty}^{\infty} \tilde{a}_k = 1!$$

DWT for Data on Bounded Interval

August-17-08
5:25 PM

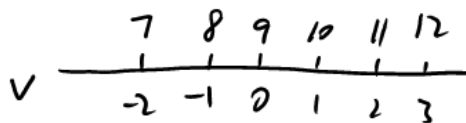
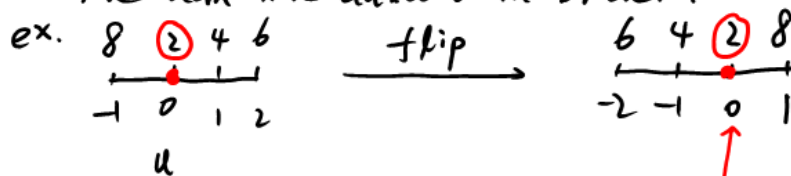
1. Suppose that data V has support $[M_{\min}, M_{\max}]$ and filter u has support $[N_{\min}, N_{\max}]$.

Then $V * u$ has support $[M_{\min} - N_{\max}, M_{\max} - N_{\min}]$ and its total length is

$$\begin{aligned} (M_{\max} - N_{\min}) - (M_{\min} - N_{\max}) &= (M_{\max} - M_{\min}) \\ &\quad + (N_{\max} - N_{\min}) \\ &= \text{Length}(V) + \text{Length}(u) \end{aligned}$$

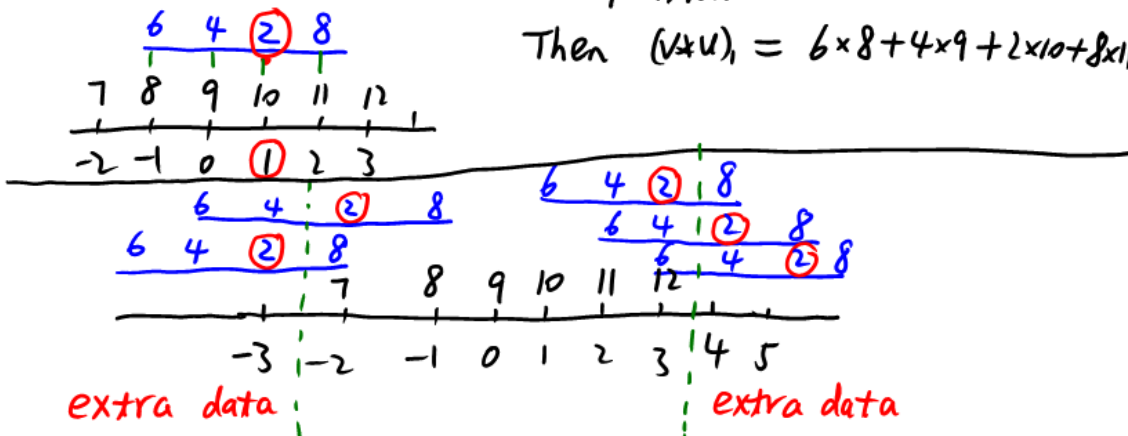
This will cause some problem

Recall that to calculate $V * u$, one first flip the filter u , then scan the data V in order:

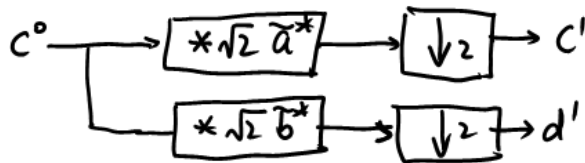


To calculate $(V * u)_1$, put the center of the flipped u at position 1

Then $(V * u)_1 = 6 \times 8 + 4 \times 9 + 2 \times 10 + 8 \times 11$



In the nonredundant case: $L=1$, we have



Due to down sampling by 2, the $\text{length}(c') \approx \frac{1}{2} \text{length}(c^0)$
and the $\text{length}(d') \approx \frac{1}{2} \text{length}(c^0)$

$$\text{so } \text{length}(c') + \text{length}(d') \approx \text{length}(c^0).$$

However, due to the filter length of $\bar{a}$ and $\bar{b}$, the exact length relation is

$$\text{length}(c') + \text{length}(d') = \text{length}(c^0) + \text{lengthExtra},$$

with

lengthExtra more or less only depends on the length of filters $\bar{a}$ and $\bar{b}$. Quite often $\text{lengthExtra} > 0$ (Except the Haar filter for $\text{length}(c^0)$ a power of 2).

In other words, even for the smallest nonredundant case $L=1$, for data of length n , the total number of all wavelet coefficients $> n$. This is not desirable in

many applications: *We need extra storage for the extra wavelet coefficients. if we just pad the outside boundary by 0.*



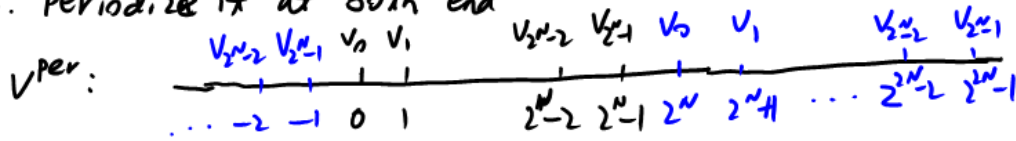
How can we handle the extra wavelet coefficients for DWT for data sitting on a bounded interval?

2. Deal data boundary by periodizing the data

1. Assume that our data V has support $[0, 2^N - 1]$.



2. Periodize it at both end



3 Then V^{per} is 2^N -periodic: $V_{k+2^N}^{per} = V_k^{per}$.

Instead of considering $\sqrt{2} T_{\alpha, 2} V$, we consider

$$\sqrt{2} T_{\alpha, 2} V^{per}$$

It is not difficult to check that $\sqrt{2} T_{\alpha, 2} V^{per}$ is 2^{N+1} -periodic.

4 We use $\sqrt{2} T_{\alpha, 2} V^{per}$ restricted to $[0, 2^{N+1} - 1]$ instead of $\sqrt{2} T_{\alpha, 2} V$ which has length $\geq 2^{N+1}$.

5 If we denote $c'^{per} := \sqrt{2} T_{\alpha, 2} c^{per} |_{[0, 2^{N+1} - 1]}$ and

$$d'^{per} := \sqrt{2} T_{\beta, 2} c^{per} |_{[0, 2^{N+1} - 1]}.$$

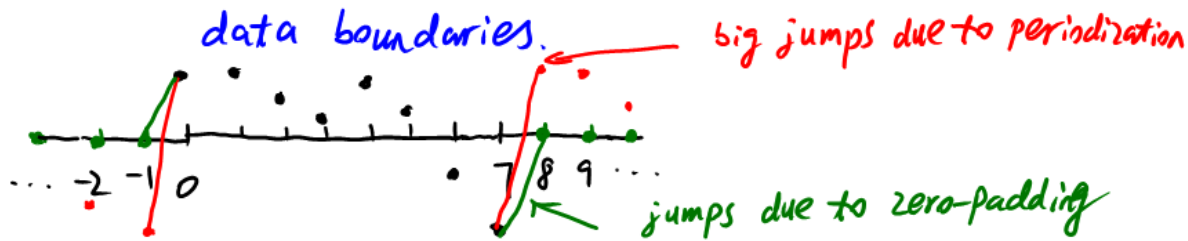
Then we still keep:

$$\text{length}(c'^{per}) + \text{length}(d'^{per}) = 2^N = \text{length}(c^0)$$

In essence, we are applying periodic wavelet transform to periodic data!

3 problems about zero-padding and periodization:

We introduce extra jumps/discontinuity at data boundaries.



Big jumps near boundaries introduce large highpass wavelet coefficients near boundaries!

4 linear-phase and symmetry of data and filters.

Let $f \in L_1(\mathbb{R})$ be an integrable function. Its Fourier transform is defined to be:

$$\hat{f}(\xi) := \int_{\mathbb{R}} f(t) e^{-it\xi} dt, \quad \xi \in \mathbb{R}.$$

For any complex number $c \in \mathbb{C}$, we can write

$$c = |c| e^{ip_c}, \quad |c| \geq 0 \text{ is its magnitude and } p_c \in \mathbb{R} \text{ is its phase}$$

For a function $f \in L_1(\mathbb{R})$, we say that f is of (strict) linear phase if

$$\hat{f}(\xi) = |\hat{f}(\xi)| e^{iP_f(\xi)} \quad \text{and } P_f(\xi) \text{ is a linear function (taking real value), that is,}$$

$$P_f(\xi) = c_1 + c_2 \xi, \quad \forall \xi \in \mathbb{R} \text{ for some } c_1, c_2 \in \mathbb{R}.$$

More generally, we say that f is of linear phase if

$$\hat{f}(\xi) = A(\xi) e^{i(c_1 + c_2 \xi)} \quad \forall \xi \in \mathbb{R} \text{ for } A(\xi), c_1, c_2 \in \mathbb{R}. \quad *$$

That is, we allow the magnitude to be all real numbers.

If (*) holds, then

$$\overline{\hat{f}(\xi)} = A(\xi) e^{-i(c_1 + c_2 \xi)}.$$

That is, we must have

$$\widehat{f}(\xi) e^{-i(c_1 + c_2 \xi)} = A(\xi) = \overline{\widehat{f}(\xi)} e^{i(c_1 + c_2 \xi)}$$

So we must have

$$\overline{\widehat{f}(\xi)} = \widehat{f}(\xi) e^{-i2(c_1 + c_2 \xi)}$$

In the time domain, since

$$\begin{aligned} \widehat{f(-\cdot)}(\xi) &= \int_{\mathbb{R}} \overline{f(-t)} e^{-i\xi t} dt = \overline{\int_{\mathbb{R}} f(-t) e^{i\xi t} dt} \\ &= \overline{\int_{\mathbb{R}} f(t) e^{-i\xi t} dt} = \overline{\widehat{f}(\xi)} \end{aligned}$$

$$\begin{aligned} \widehat{f(\cdot - 2c_1)}(\xi) &= \int_{\mathbb{R}} f(t - 2c_1) e^{-i\xi t} dt = \int_{\mathbb{R}} f(t) e^{-i(t + 2c_1)\xi} dt \\ &= e^{-i2c_1\xi} \widehat{f}(\xi) \end{aligned}$$

We have $\widehat{f(-\cdot)}(\xi) = e^{-i2c_1\xi} \widehat{f(\cdot - 2c_1)}(\xi)$

That is, we must have

$$\overline{f(-t)} = e^{-i2c_1\xi} f(t - 2c_1) \quad \forall t \text{ (r.a.e. } t)$$

Re write it, we have

$$\overline{e^{-ic_1\xi} f(-t)} = e^{-ic_1\xi} f(t - 2c_1)$$

Denote $g(t) := e^{-ic_1\xi} f(t)$. Then

$$\overline{g(-t)} = g(t - 2c_1) \text{ with } g(t) := e^{-ic_1\xi} f(t).$$

Note that f is a real valued function

$$\iff \overline{\widehat{f}(\xi)} = \widehat{f}(-\xi)$$

Now we discuss linear-phase property for real-valued functions:

By $\widehat{f}(\xi) = \int_{\mathbb{R}} f(t) e^{-i\xi t} dt$, we have

$$\widehat{f}^{(n)}(0) = \int_{\mathbb{R}} f(t) (-it)^n dt = (i)^n \int_{\mathbb{R}} f(t) t^n dt$$

Assuming $\widehat{f}(\xi) = \frac{\widehat{f}^{(n)}(0)}{n!} \xi^n + o(|\xi|^n)$, $\xi \rightarrow 0$

with $\widehat{f}^{(n)}(0) \neq 0$.

By $\overline{\hat{f}(\xi)} = \hat{f}(\xi) e^{-i2(c_1 + c_2 \xi)}$

We have $\frac{\overline{\hat{f}^{(n)}(0)}}{n!} \xi^n = \frac{\hat{f}^{(n)}(0)}{n!} \xi^n e^{-i(2c_1 + 2c_2 \xi)} + o(\xi^n)$

That is, $\overline{\hat{f}^{(n)}(0)} = \hat{f}^{(n)}(0) e^{-i2c_1}$

Since $\hat{f}^{(n)}(0) = (-i)^n \underbrace{\int_{\mathbb{R}} f(x) x^n dx}_{\text{real number}}$

We must have $\overline{(-i)^n} = (-i)^n e^{-i2c_1} \Rightarrow$
 $(-1)^n (-i)^n = (-i)^n e^{-i2c_1} \Rightarrow e^{-i2c_1} = (-1)^n$

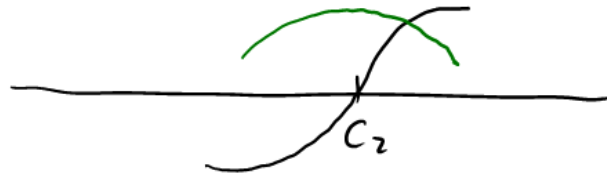
That is $\overline{\hat{f}(\xi)} = \hat{f}(\xi) e^{-i2c_2 \xi}$ or $\overline{\hat{f}(\xi)} = -\hat{f}(\xi) e^{-i2c_2 \xi}$

In other words,

$$f(-x) = \pm f(x - 2c_2).$$

That is, f is either symmetric or antisymmetric about c_2 by

$$f(-c_2) = \pm f(c_2 - 2c_2) = \pm f(c_2)$$

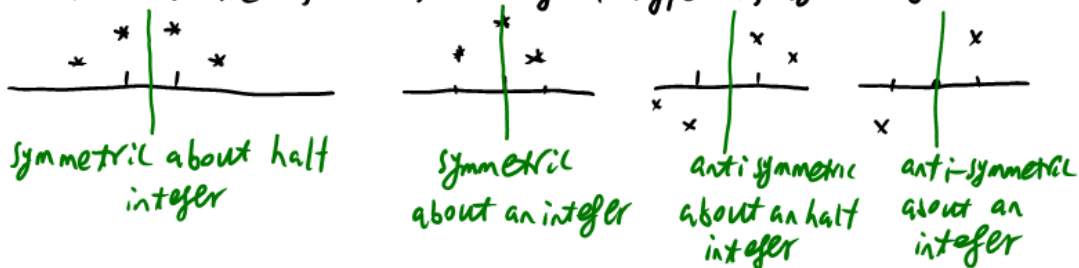


Conclusion: For a real-value (compactly supported) function f ,
 f is of linear-phase $\iff f$ has symmetry (symmetric or antisymmetric)

Same conclusion holds for sequence s :

For $u: \mathbb{Z} \rightarrow \mathbb{R}$, u is of linear phase if and only if

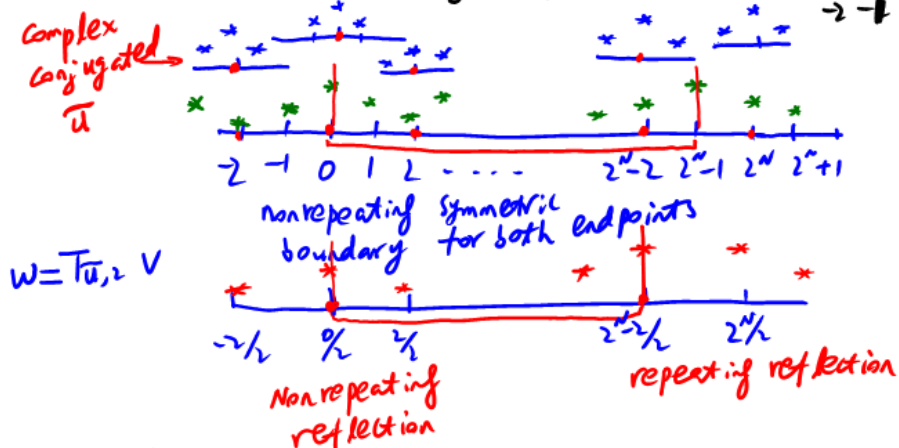
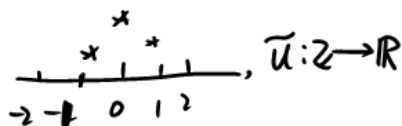
u has one of the following 4 types of symmetry:



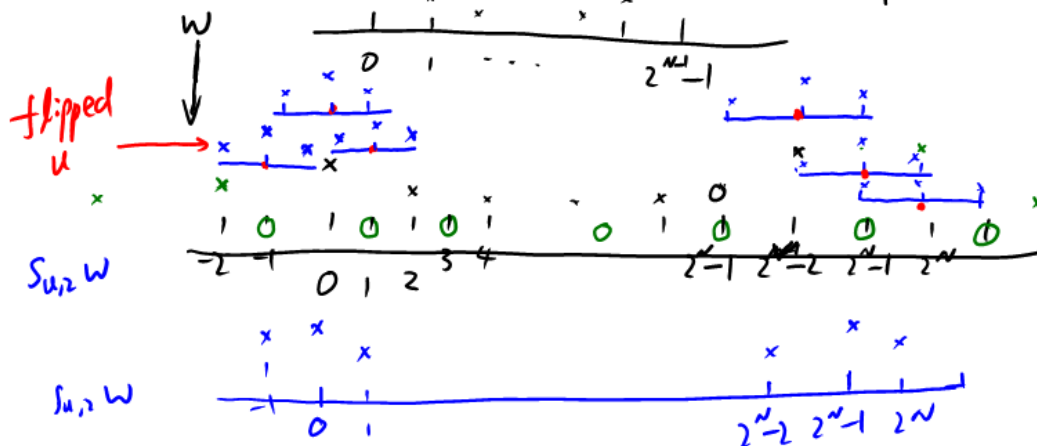
linear phase is known to reduce artifact since human eyes are sensitive to non-symmetric objects

5 DWT for filters with symmetry

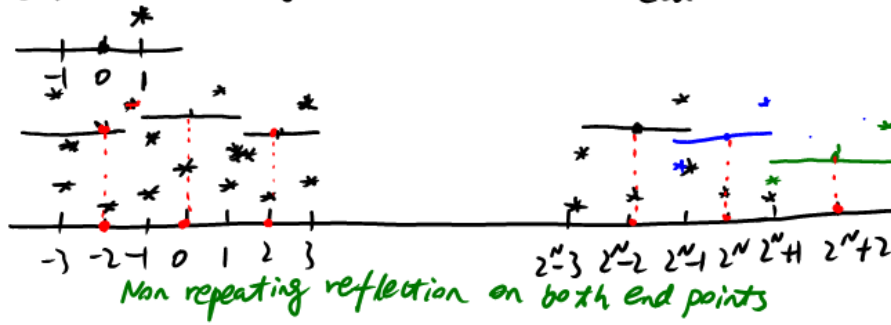
Case 1: $\tilde{u}$ is symmetric about 0



u has the same symmetry as $\tilde{u}$: u



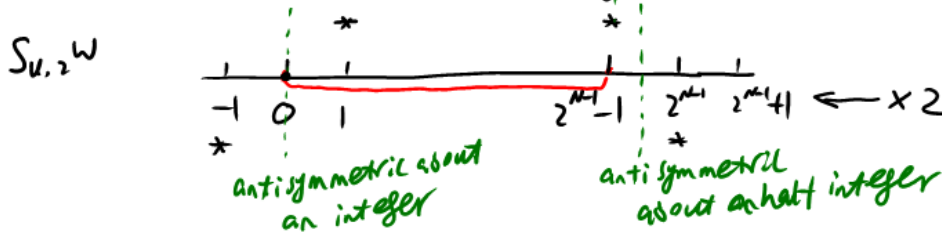
Case 2: u is antisymmetric about 0 (Real-valued filter)



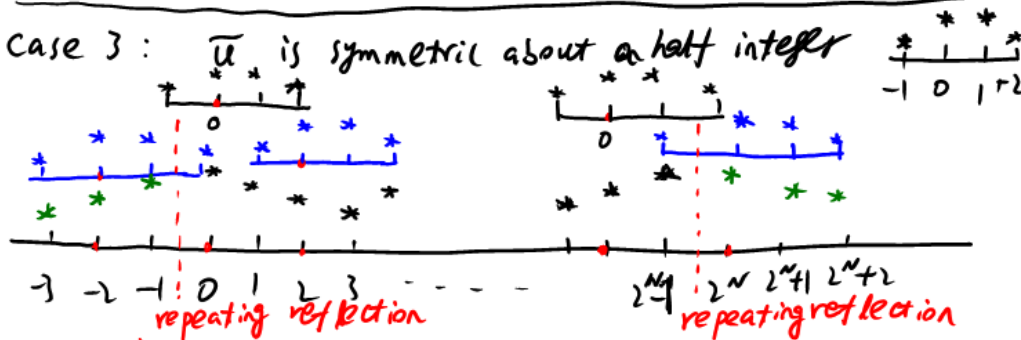
$$W = T_{u,2} V$$



$\bar{u}$ and u have the same symmetry type

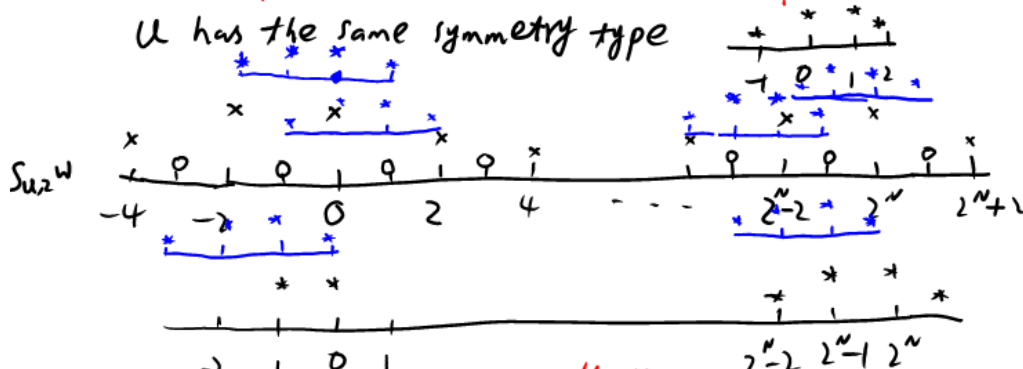


Case 3: $\bar{u}$ is symmetric about a half integer



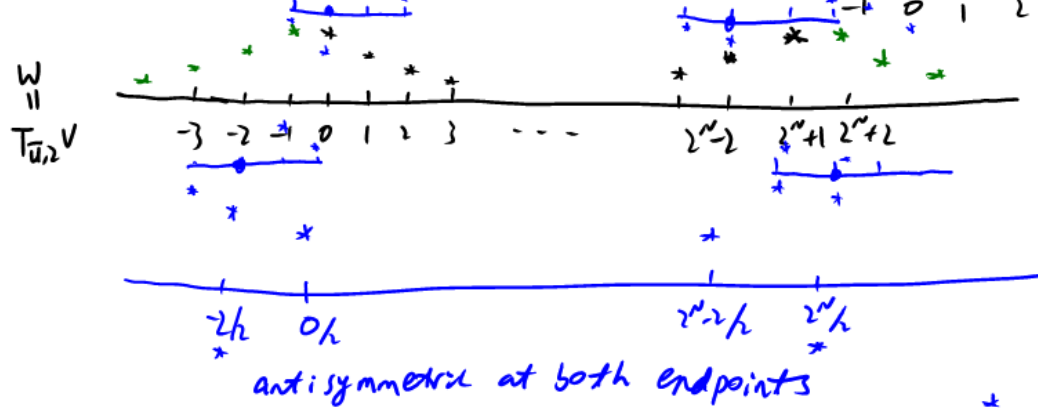
$$W = T_{u,2} V$$

u has the same symmetry type

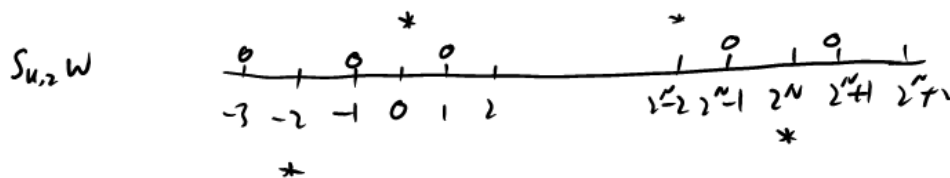


Repeating reflection on both endpoints

Case 4: u is antisymmetric about a half integer



u has the same symmetry type as u :



Summary

Filter	Decomposition		Reconstruction	
	Left pt	Right pt	Left pt	Right pt