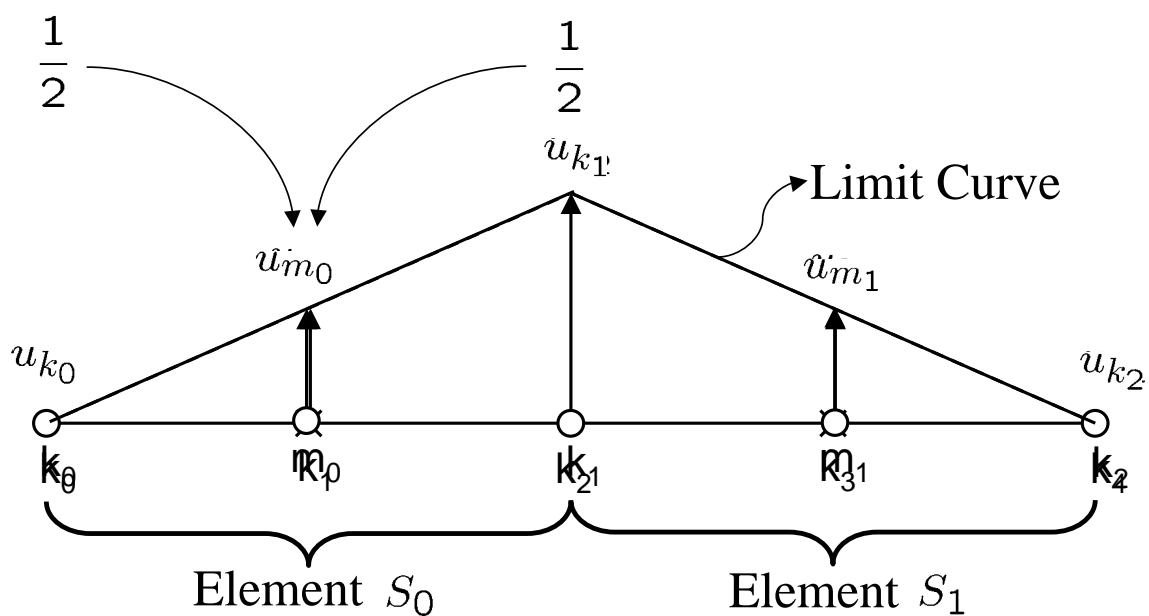


Simple Linear Interpolation



$$(u_{k_0} + u_{k_1}z^{-2} + u_{k_2}z^{-4}) \times \left(\frac{1}{2}z + 1 + \frac{1}{2}z^{-1}\right) =$$

$$\frac{1}{2}u_{k_0}z + u_{k_0} + \frac{1}{2}(u_{k_0} + u_{k_1})z^{-1} + u_{k_1}z^{-2} + \frac{1}{2}(u_{k_1} + u_{k_2})z^{-3} + u_{k_2}z^{-4} + \frac{1}{2}u_{k_2}z^{-5}$$

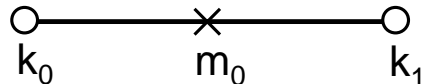
Unchanged

Interpolating Subdivision Schemes

- Given a set of data $\{u_{j,k_0}, u_{j,k_1}, \dots, u_{j,k_N}\}$, find filters $h_j[k, m]$ such that:

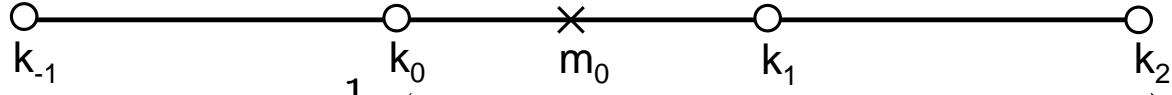
$$\left. \begin{aligned} u_{j+1,k} &= u_{j,k} \\ u_{j+1,m} &= \sum_{k \in N(j,m)} h_j[k, m] u_{j,k} \end{aligned} \right\} \underline{u}_{j+1} = \mathbf{S} \underline{u}_j$$

- e.g. two point (linear) scheme



$$u_{j+1,m_i} = \frac{1}{2} (u_{j,k_i} + u_{j,k_{i+1}})$$

four point (cubic) scheme

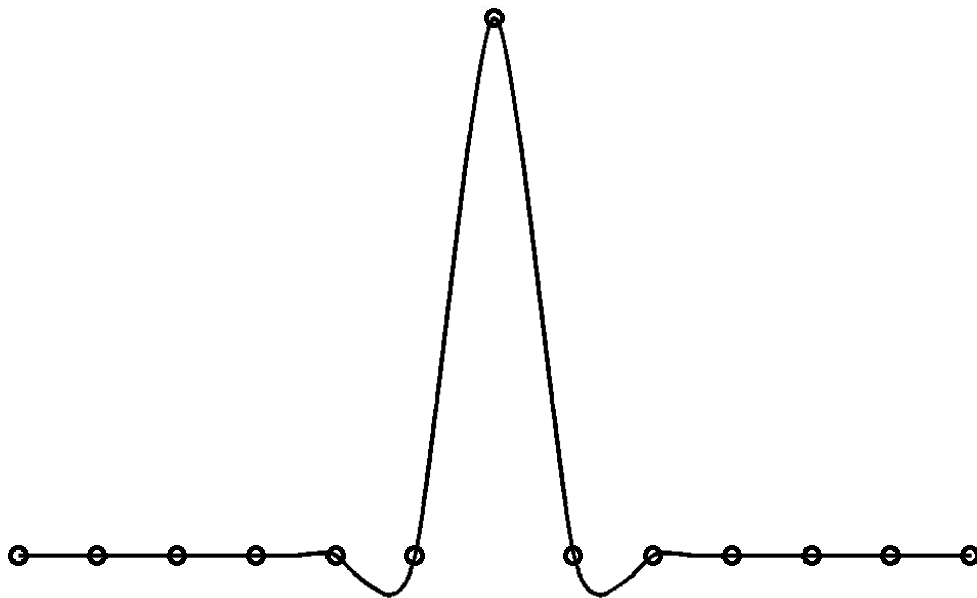


$$u_{j+1,m_i} = \frac{1}{16} (-u_{j,k_{i-1}} + 9u_{j,k_i} + 9u_{j,k_{i+1}} - u_{j,k_{i+2}})$$

- Generalizes easily to multiple dimensions, non-uniformly spaced points, boundaries, etc.

Interpolating Subdivision Schemes

- Limit curve is an interpolating function



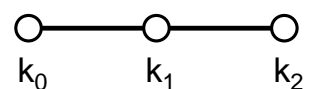
Wavelets From Subdivision

- Limit curves can be used to interpolate data.

On coarse grid

$$f_j(x) = \sum_{k \in \mathcal{K}(j)} u_{j,k} \varphi_{j,k}(x)$$

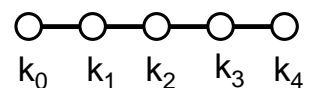
$$\mathcal{K}(j) = \{k_0, k_1, \dots\}$$



On fine grid

$$f_{j+1}(x) = \sum_{l \in \mathcal{K}(j+1)} u_{j+1,l} \varphi_{j+1,l}(x)$$

$$\mathcal{K}(j+1) = \{k_0, m_0, k_1, \dots\}$$

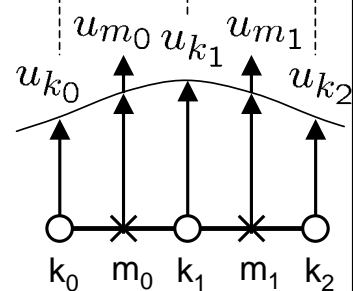


Suppose that $u_{j+1,l}$ is coarsened by subsampling

$$u_{j,k} = u_{j+1,k}$$

and remaining data is predicted using subdivision

$$u_{j,m} = u_{j+1,m} - \sum_{k \in N(j,m)} h_j[k, m] u_{j,k}$$



Wavelets From Subdivision

- Does this fit the wavelet framework?

$$\begin{aligned}
 f_{j+1}(x) &= \sum_{l \in \mathcal{K}(j+1)} u_{j+1,l} \varphi_{j+1,l}(x) && \text{fine approximation} \\
 &= \underbrace{\sum_{k \in \mathcal{K}(j)} u_{j,k} \varphi_{j,k}(x)}_{\text{coarse approximation}} + \underbrace{\sum_{m \in \mathcal{M}(j)} u_{j,m} w_{j,m}(x)}_{\text{details}}
 \end{aligned}$$

If we set $u_{j,k} = 0$, $u_{j,m} = \delta_{m,m'}$, our coarsening/prediction strategy gives

$$\begin{aligned}
 u_{j+1,k} &= u_{j,k} && = 0 \\
 u_{j+1,m} &= u_{j,m} + \sum_{k \in N(j,m)} h_j[k, m] u_{j,k} && = \delta_{m,m'}
 \end{aligned}$$

So the “wavelets” are

$$w_{j,m}(x) = \varphi_{j+1,m}(x)$$

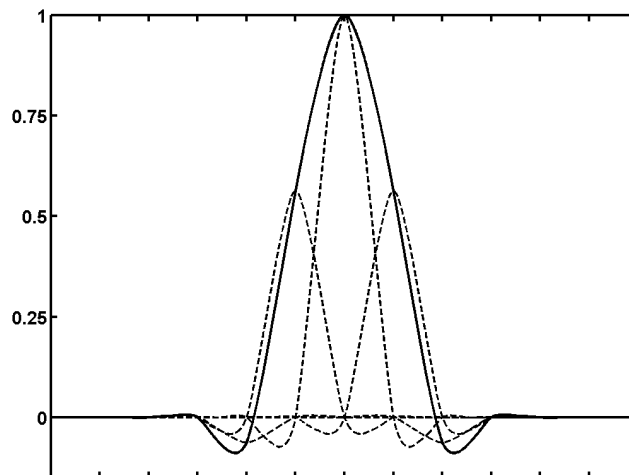
Wavelets From Subdivision

- Similarly, setting $u_{j,k} = \delta_{k,k'}$, $u_{j,m} = 0$

$$\begin{aligned} u_{j+1,k} &= u_{j,k} & &= \delta_{k,k'} \\ u_{j+1,m} &= \sum_{k \in N(j,m)} h_j[k, m] u_{j,k} & &= h_j[k', m] \end{aligned}$$

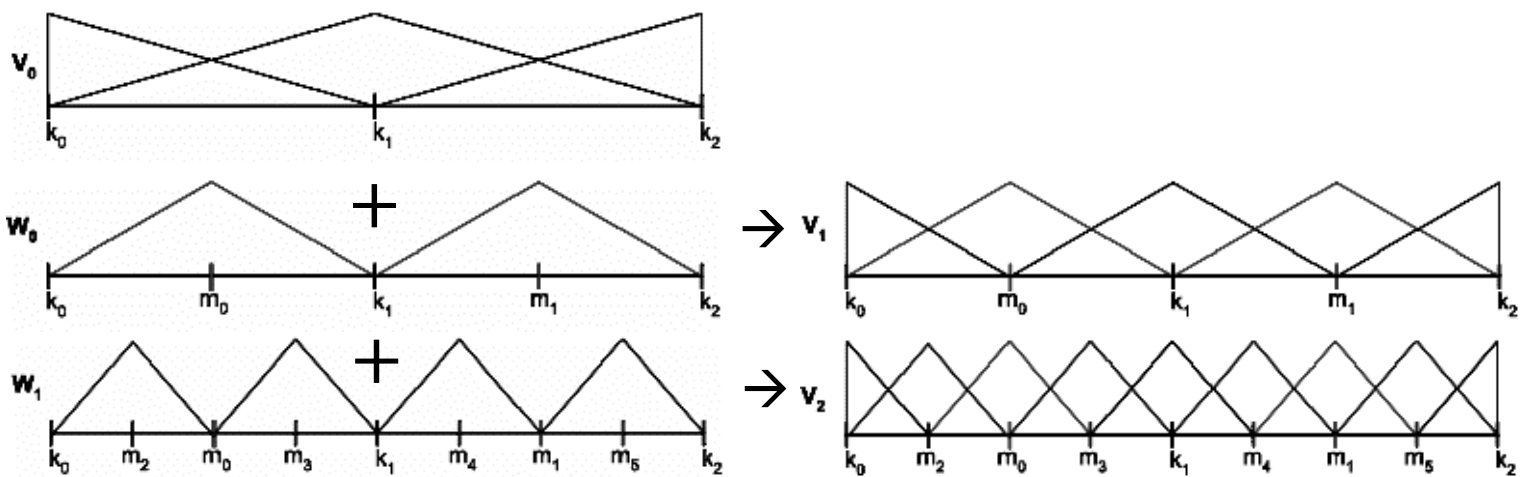
produces the refinement equation:

$$\varphi_{j,k}(x) = \varphi_{j+1,k}(x) + \sum_{m \in n(j,k)} h_j[k, m] \varphi_{j+1,m}(x)$$



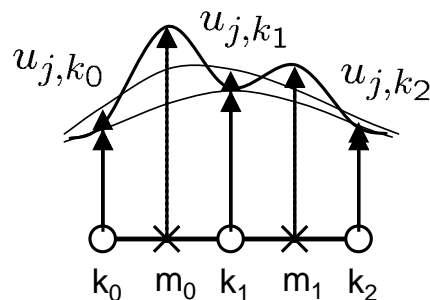
Wavelets From Subdivision

- So subdivision schemes naturally lead to hierarchical bases



Wavelets From Subdivision

- The coarsening strategy $u_{j,k} = u_{j+1,k}$ is generally less than ideal – some smoothing (antialiasing) desirable



Accomplished by forcing the wavelet to have one or more vanishing moments

$$\int w_{j,m}(x)x^k dx = 0, \quad k = 0, 1, \dots, p-1$$

Larger p means smaller coefficients $u_{j,m}$ in wavelet series

$$f(x) = \sum_{k \in \mathcal{K}(j)} u_{j,k} \varphi_{j,k}(x) + \sum_{j=0}^{\infty} \sum_{m \in \mathcal{M}(j)} u_{j,m} w_{j,m}(x)$$

$$u_{j,m} \sim h_j^p f^{(p)}(x_m)$$

Wavelets From Subdivision

- How to improve wavelets using lifting

$$w_{j,m}^{new}(x) = w_{j,m}(x) - \sum_{k \in \mathcal{K}(j)} s_j[k, m] \varphi_{j,k}(x)$$

$\varphi_{j,k}(x)$ as before → tunable parameters

Choose $s_j[k, m]$ to make the moments zero.

- Regardless of the choice for $s_j[k, m]$, $\varphi_{j,k}(x)$ and $w_{j,m}^{new}(x)$ are orthogonal to the dual functions

$$\tilde{w}_{j,m}^{new}(x) = \tilde{\varphi}_{j+1,m}^{new}(x) - \sum_{k \in \mathcal{N}(j,m)} h_j[k, m] \tilde{\varphi}_{j+1,k}^{new}(x)$$

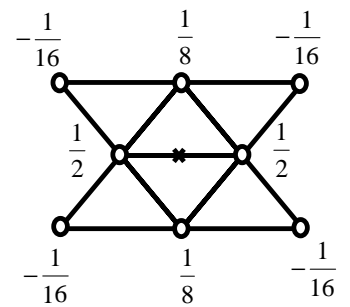
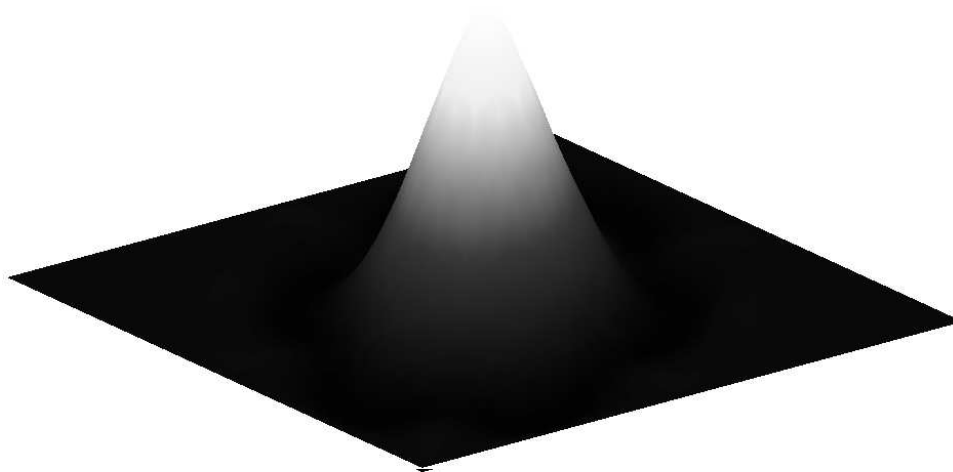
$$\tilde{\varphi}_{j,k}^{new}(x) = \tilde{\varphi}_{j+1,k}^{new}(x) + \sum_{m \in \mathcal{M}(j)} s_j[k, m] \tilde{w}_{j,m}^{new}(x)$$

from which we obtain an improved coarsening strategy:

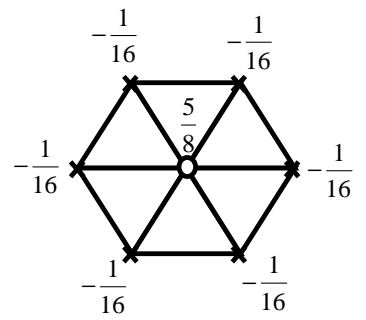
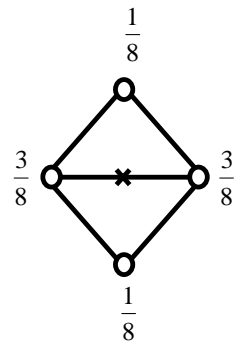
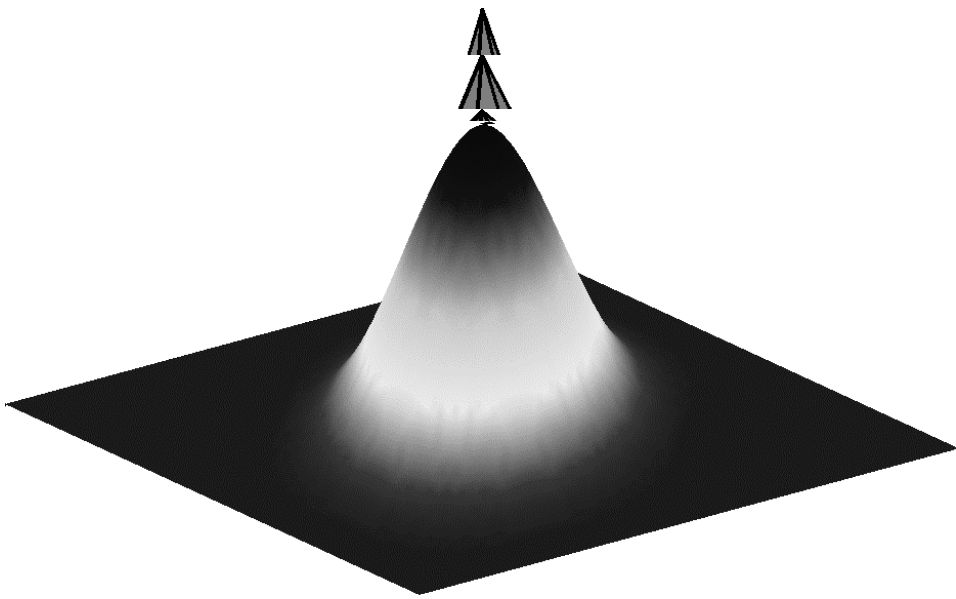
$$u_{j,m} = u_{j+1,m} - \sum_{k \in \mathcal{N}(j,m)} h_j[k, m] u_{j+1,k} \quad \text{Predict as before}$$

$$u_{j,k} = u_{j+1,k} + \sum_{m \in \mathcal{M}(j)} s_j[k, m] u_{j,m} \quad \text{Then update}$$

Butterfly Subdivision

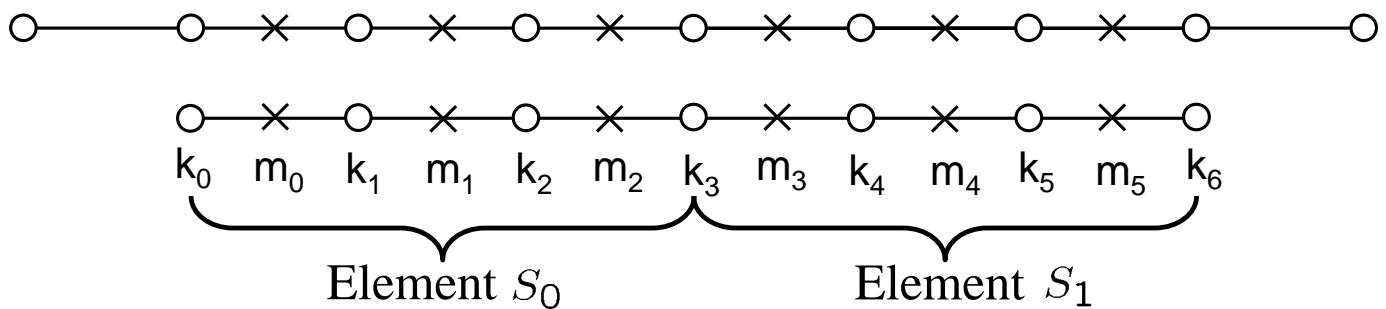


Loop Subdivision



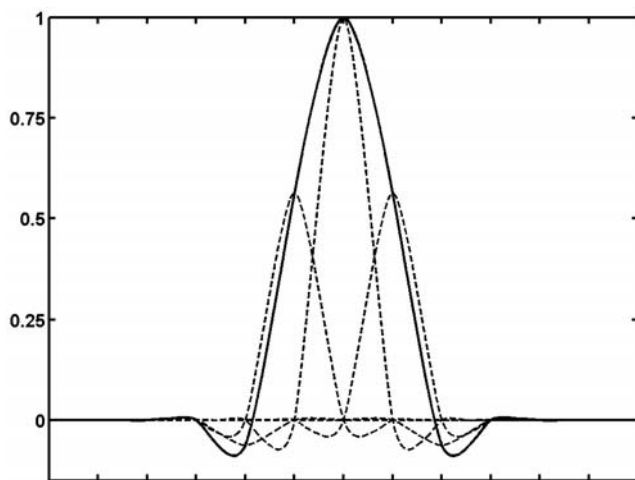
Finite Elements From Subdivision

- Key difference: subdivision mask is varied so that prediction operation is confined *within* an element



- Limit functions are finite element shape functions

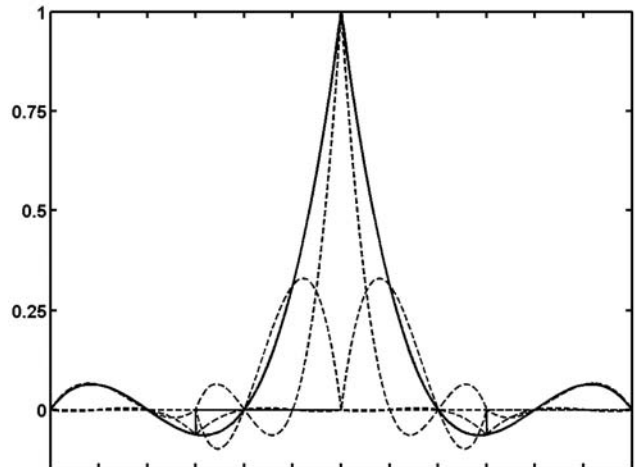
Finite Elements From Subdivision



Finite Element generated from vector subdivision - piecewise polynomial, but lacks smoothness at element boundaries

Scalar subdivision

$$\frac{1}{16} \{-1, 0, 9, 16, 9, 0, -1\}$$



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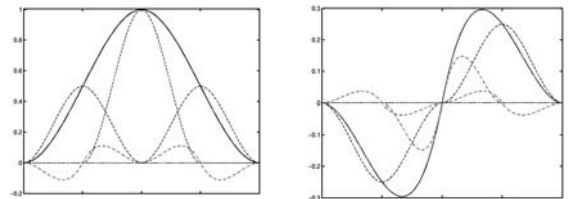
Smoother vector subdivision schemes also possible

Vector Refinement

- e.g. vector refinement relation for Hermite interpolation functions

$$\begin{Bmatrix} \varphi_{j,k}^u(x) \\ \varphi_{j,k}^\theta(x) \end{Bmatrix} = \begin{Bmatrix} \varphi_{j+1,k}^u(x) \\ \varphi_{j+1,k}^\theta(x) \end{Bmatrix} + \sum_{m \in n(j,k)} \mathbf{H}_j[k,m] \begin{Bmatrix} \varphi_{j+1,m}^u(x) \\ \varphi_{j+1,m}^\theta(x) \end{Bmatrix}$$

$$\mathbf{H}_j[k,m] = \begin{bmatrix} \varphi_k^u(x_m) & \frac{d\varphi_k^u(x_m)}{dx} \\ \varphi_k^\theta(x_m) & \frac{d\varphi_k^\theta(x_m)}{dx} \end{bmatrix}$$



Cubic subdivision for displacements and rotations

- Wavelets

$$\begin{Bmatrix} w_{j,m}^u(x) \\ w_{j,m}^\theta(x) \end{Bmatrix} = \begin{Bmatrix} \varphi_{j+1,m}^u(x) \\ \varphi_{j+1,m}^\theta(x) \end{Bmatrix} - \sum_{k \in A(j,m)} \mathbf{S}_j^T[k,m] \begin{Bmatrix} \varphi_{j,k}^u(x) \\ \varphi_{j,k}^\theta(x) \end{Bmatrix}$$

$$\sum_{k \in A(j,m)} \left[\int_S x^i \{ \varphi_{j,k}^u(x) \quad \varphi_{j,k}^\theta(x) \} dx \right] \mathbf{S}_j[k,m] = \int_S x^i \{ \varphi_{j+1,m}^u(x) \quad \varphi_{j+1,m}^\theta(x) \} dx$$

