

## Laplacian Basics (Smoothing, Cotangent Laplacian)

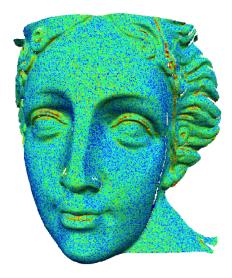
Instructor: Hao Su

#### UC San Diego

## MESH SMOOTHING (AKA DENOISING, FILTERING, FAIRING)

## **Mesh Smoothing**

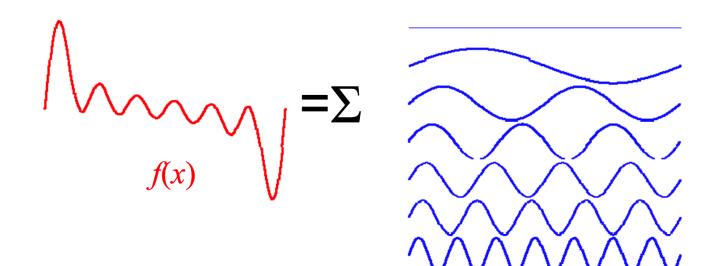
- Input: Noisy mesh (scanned or other)
- Output: Smooth mesh
- How: Filter out high frequency noise





### **Smoothing by Filtering**

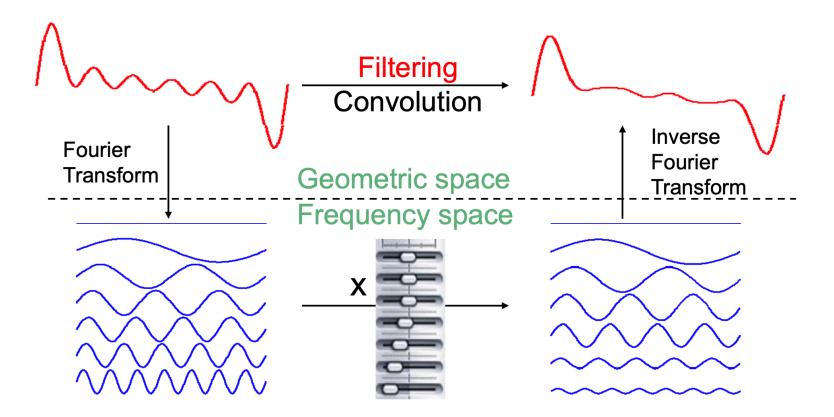
**Fourier Transform** 



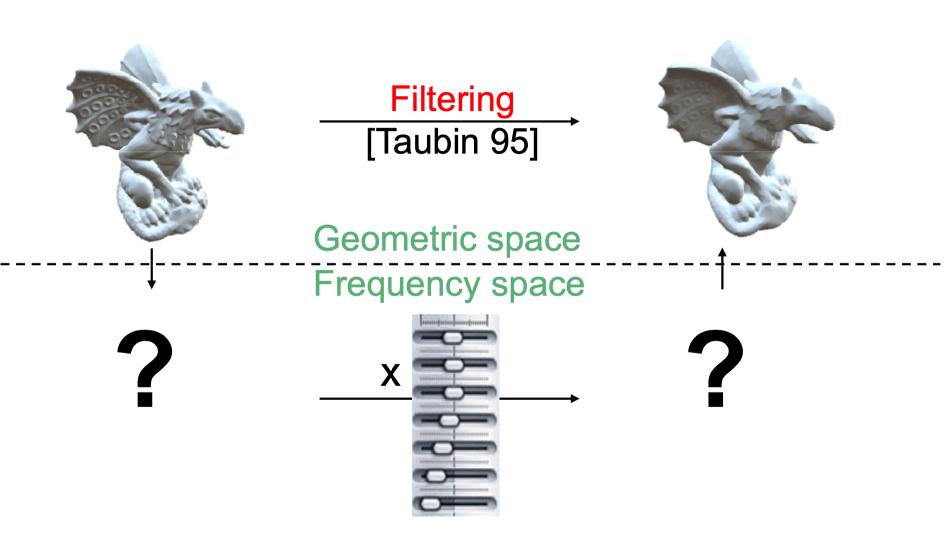
sin(kx)

## **Smoothing by Filtering**

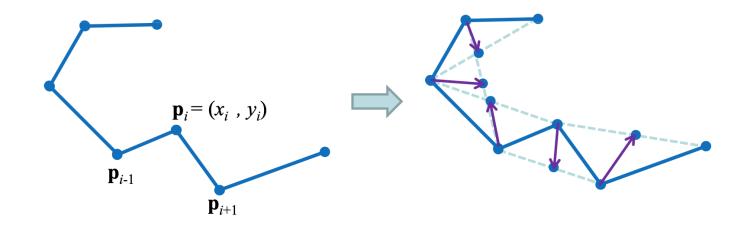
#### **Fourier Transform**



#### **Filtering on a Mesh**

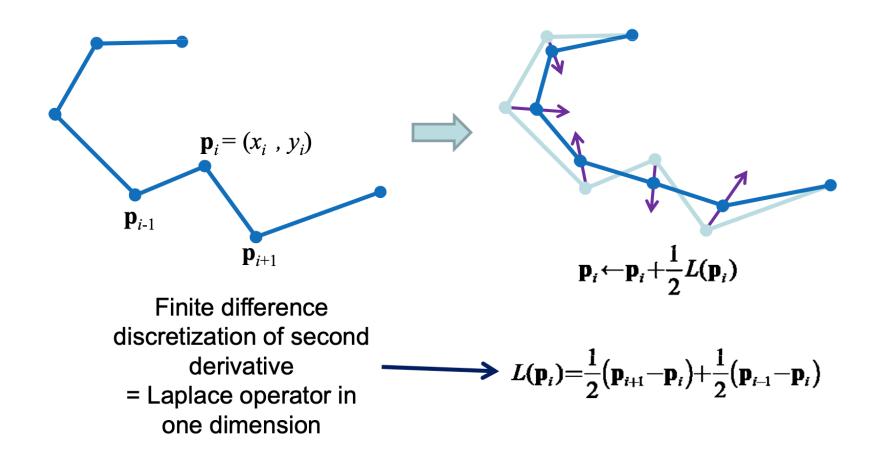


• An easier problem: How to smooth a curve?



$$(\mathbf{p}_{i-1} + \mathbf{p}_{i+1})/2 - \mathbf{p}_i$$
$$L(\mathbf{p}_i) = \frac{1}{2} (\mathbf{p}_{i+1} - \mathbf{p}_i) + \frac{1}{2} (\mathbf{p}_{i-1} - \mathbf{p}_i)$$

• An easier problem: How to smooth a curve?



<u>Algorithm:</u> Repeat for *m* iterations (for non boundary points):

 $\mathbf{p}_i \leftarrow \mathbf{p}_i + \lambda L(\mathbf{p}_i)$ 

For which  $\lambda$ ?  $0 < \lambda < 1$ 

Closed curve converges to? Single point

#### **Spectral Analysis**

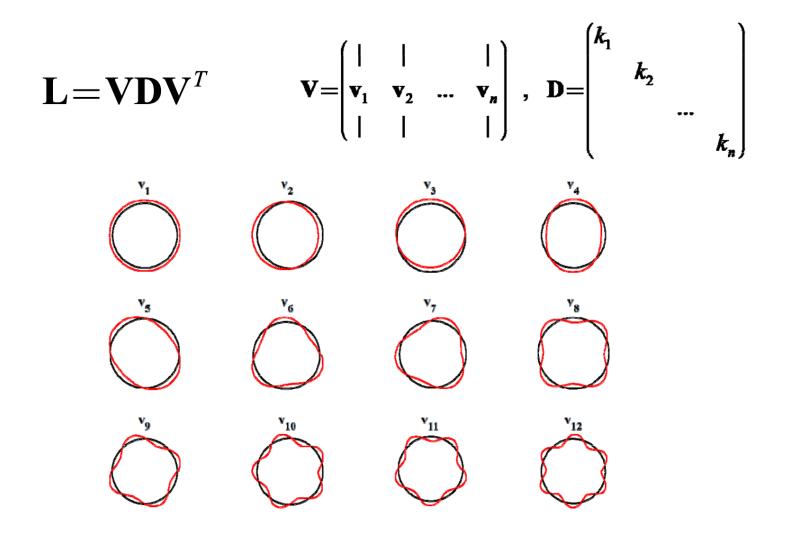
Closed curve

Re-write 
$$\mathbf{p}_{i}^{(t+1)} = \mathbf{p}_{i}^{(t)} + \lambda L(\mathbf{p}_{i}^{(t)})$$
  
 $L(\mathbf{p}_{i}) = \frac{1}{2}(\mathbf{p}_{i+1} - \mathbf{p}_{i}) + \frac{1}{2}(\mathbf{p}_{i-1} - \mathbf{p}_{i})$ 

in matrix notation:  $\mathbf{P}^{(t+1)} = \mathbf{P}^{(t)} - \lambda \mathbf{L} \mathbf{P}^{(t)}$ 

$$\mathbf{P} = \begin{pmatrix} x_1 & y_2 \\ \dots & \dots \\ x_n & y_n \end{pmatrix} \in \mathbb{R}^{n \times 2} \quad \mathbf{L} = \frac{1}{2} \begin{pmatrix} 2 & -1 & & & -1 \\ -1 & 2 & -1 & & \\ & & \dots & & \\ & & & -1 & 2 & -1 \\ -1 & & & & -1 & 2 \end{pmatrix} \in \mathbb{R}^{n \times n}$$

### The Eigenvectors of $\boldsymbol{L}$



#### $0 \le \lambda(L) \le 2$

**Lemma 5.3.1.** The Laplacian of  $R_n$  has eigenvectors

 $egin{aligned} oldsymbol{x}_k(u) &= \cos(2\pi k u/n), \ and \ oldsymbol{y}_k(u) &= \sin(2\pi k u/n), \end{aligned}$ 

for  $0 \le k \le n/2$ , ignoring  $\mathbf{y}_0$  which is the all-zero vector, and for even n ignoring  $\mathbf{y}_{n/2}$  for the same reason. Eigenvectors  $\mathbf{x}_k$  and  $\mathbf{y}_k$  have eigenvalue  $2 - 2\cos(2\pi k/n)$ .

#### **Spectral Analysis**

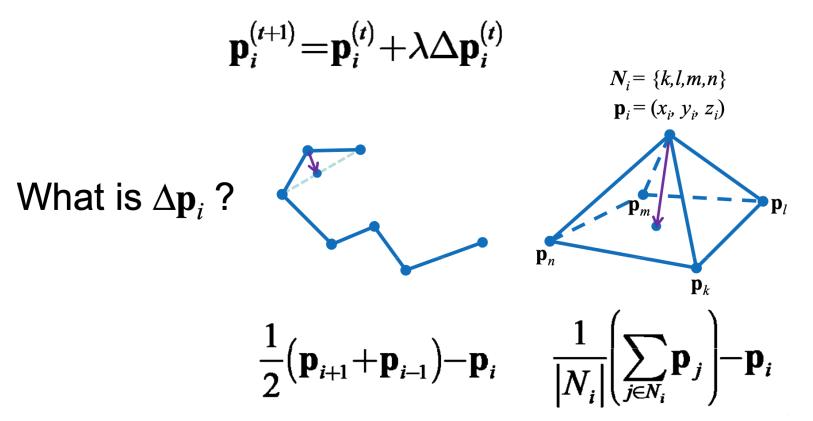
Then: 
$$\mathbf{P}^{(t+1)} = \mathbf{P}^{(t)} - \lambda \mathbf{L} \mathbf{P}^{(t)} = (\mathbf{I} - \lambda \mathbf{L}) \mathbf{P}^{(t)}$$

After *m* iterations: 
$$\mathbf{P}^{(m)} = (\mathbf{I} - \lambda \mathbf{L})^m \mathbf{P}^{(0)}$$

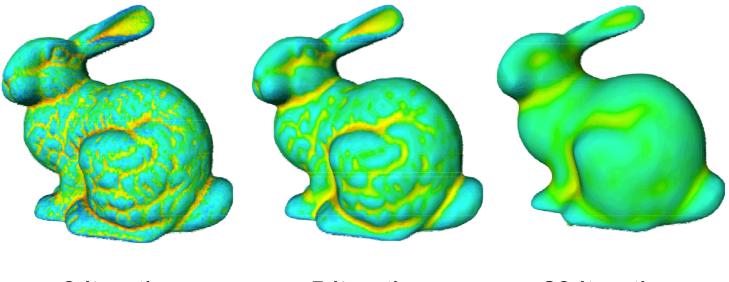
Can be described using eigendecomposition of L  $\mathbf{L} = \mathbf{V} \mathbf{D} \mathbf{V}^{T}$  $\mathbf{V} = \begin{pmatrix} I & I & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{D} = \begin{pmatrix} k_{1} & k_{2} & I \\ I & I & I \end{pmatrix}, \mathbf{$ 

#### **Laplacian Smoothing on Meshes**

Same as for curves:



#### **Laplacian Smoothing on Meshes**



0 Iterations

5 Iterations

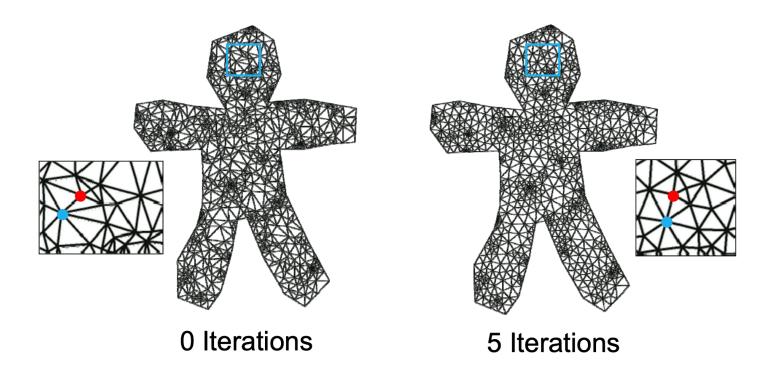
20 Iterations

$$\mathbf{p}_i^{(t+1)} = \mathbf{p}_i^{(t)} + \lambda \Delta \mathbf{p}_i^{(t)}$$

#### $\Delta \mathbf{p}_i$ = mean curvature normal

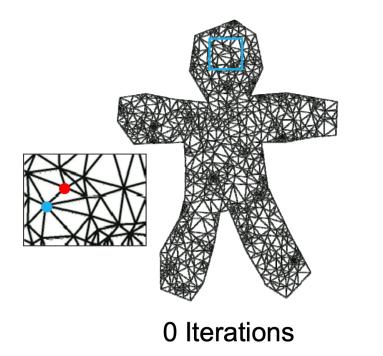
#### **Laplace Operator Discretization**

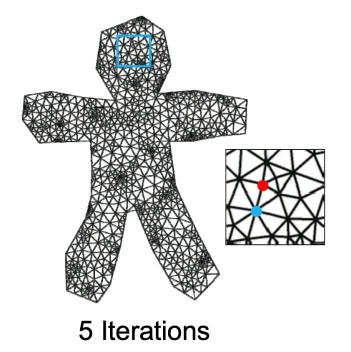
• Sanity check — what should happen if the mesh lies in the plane:  $p_i = (x_i, y_i, 0)$ ?



#### **Laplace Operator Discretization**

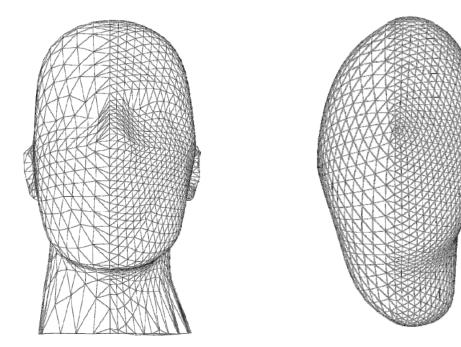
## Not good – A flat mesh is smooth, should stay the same after smoothing





#### **Laplace Operator Discretization**

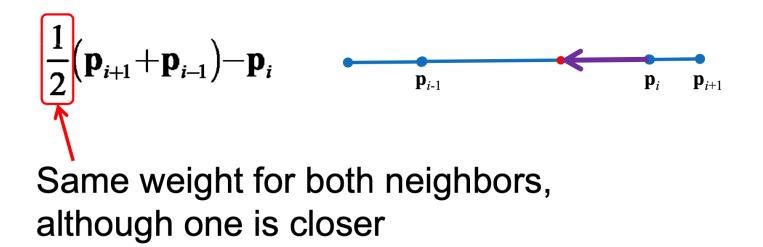
# Not good – The result should not depend on triangle sizes



From Desbrun et al., Siggraph 1999

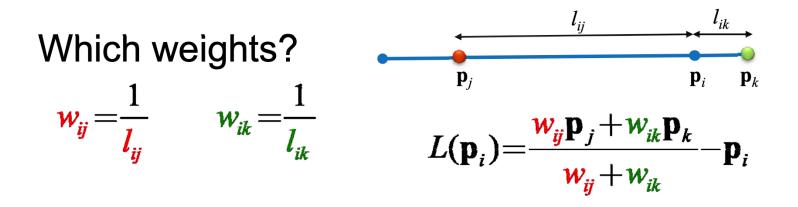
#### What Went Wrong?

Back to curves:



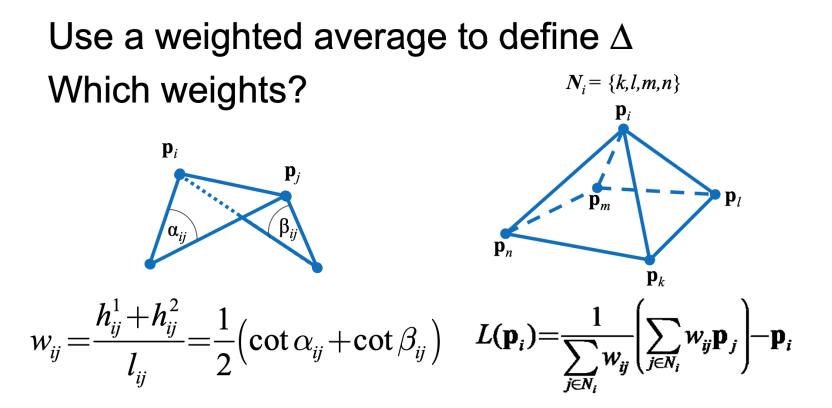
#### The Solution (1D)

Use a weighted average to define  $\Delta$ 



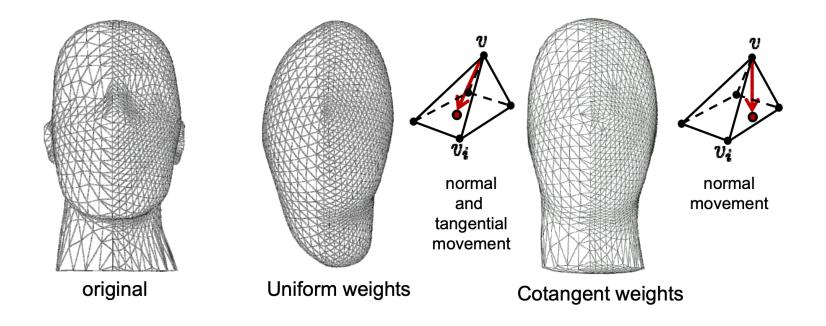
Straight curves will be invariant to smoothing

## Solution (2D)

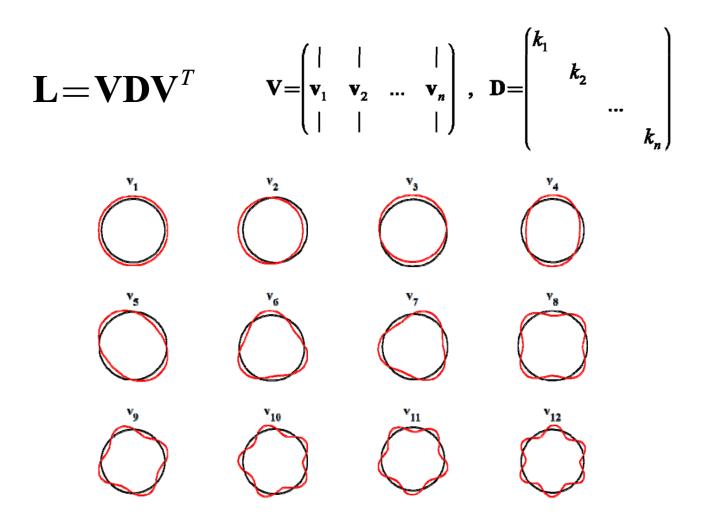


Planar meshes will be invariant to smoothing

#### **Smoothing with the Cotangent Laplacian**

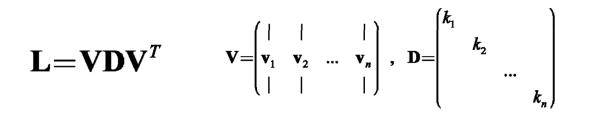


#### The Eigenvectors of L



#### **Spectral Analysis**

Cotangent Laplacian





Demo

From Vallet et al., Eurographics 2008

#### Smoothing using the Laplacian Eigendecomposition

