## Parameterization - Free Boundary



- Direct energy minimization
- Example: Least Squares Conformal Map (LSCM)....
- Indirect
- Example: Angle Based Flattening (ABF)....


LSCM [Lévy et al. 2002].
ights [Floater 2003] on a circular domain. University of British Columbia

Free vs Fixed

## LSCM - Geometric Interpretation

- Algebraic Interpretation:
- Minimize conformal energy
$E_{\mathrm{C}}=\left(\sigma_{1}-\sigma_{2}\right)^{2} / 2$
- Geometric Interpretation:
- Use triangle similarity

- Given angles $\alpha_{1}, \alpha_{2}, \alpha_{3}$ of a triangle $\mathrm{P}_{1} \mathrm{P}_{2} \mathrm{P}_{3}$ in 2D we have

$$
\begin{aligned}
& P_{3}-P_{1}=\frac{\sin \alpha_{2}}{\sin \alpha_{3}} R_{\alpha_{1}}\left(P_{2}-P_{1}\right), \\
& R_{\alpha}=\left(\begin{array}{cc}
\cos \alpha & \sin \alpha \\
-\sin \alpha & \cos \alpha
\end{array}\right)
\end{aligned}
$$

## LSCM

- In map from 3D to 2D might be impossible to keep angles exactly
- Use least-squares

$$
\min \sum_{i}\left(P_{3}^{i}-P^{i_{1}}-\frac{\sin \alpha^{i}{ }_{2}}{\sin \alpha^{i}{ }_{3}} R_{\alpha_{1}}\left(P^{i}{ }_{2}-P_{1}^{i}\right)\right)^{2}
$$

- To solve need to fix two vertices
- Obtain linear system
- Choice of vertices affects solution



## ABF: Angle Based Flattening

- Triangular 2D mesh is defined by its angles
- Formulate parameterization as problem in angle space
- Angle based formulation:
- Distortion as function of angles (conformality)
- Validity: set of angle constraints
- Convert solution to UV



## ABF Formulation



- Distortion:
- 2D/3D angle difference

$$
\sum_{t \in T, j=1.3} w_{j}^{t}\left(\alpha_{j}^{t}-\beta_{j}^{t}\right)^{2}, w_{j}^{t}=1 / \beta_{j}^{t^{2}}
$$


$\forall v \in V_{\text {int }}, \quad \sum_{(t, k) \in v^{*}} \alpha_{k}^{t}-2 \pi=0$

- Reconstruction
$\forall v \in V_{\text {int }}$

$$
\prod_{(t, k) \in v^{*}} \sin \alpha_{k \oplus 1}^{t}-\prod_{(t, k) \in v^{*}}
$$

$\sin \alpha_{k \ominus 1}^{t}=0$


- Solve - constrained optimization (Lagrange multipliers)


## Angle to UV Conversion

- Alternative 1: Use computed angles as input to LSCM
- Alternative 2: Unfolding
- Choose one edge \& place in 2D (keep length)
- Based on computed angles place third vertex of triangles sharing this edge in 2D
- Intersection of two rays
- Repeat recursively




## 2D Parameterization Summary

- Needed for many processing operations
- Distortion/Bijectivity important
- Trade-of quality/efficiency (as always...)
- Very popular topic (100+ major publications in last 10 years, less recently)
- More Issues
- Segmentation/Cutting
- Constraints



## Solution

- Use Lagrange Multipliers
$F^{*}(\alpha, \mu)=F(\alpha)+\mu_{1} g^{2}(\alpha)+\mu_{2} g^{3}(\alpha)+\mu_{3} g^{4}(\alpha)$
- Solve the min-max problem (minimum on $\alpha$, maximum on $\mu$ )
- Reached when all derivatives are zero
- Have non-linear system of equations
- Use Newton method to solve


## Minimization (Unconstrained)

- To find $x$ that minimizes $F(x)$ - find $x$ such that $F^{\prime}(x)=0$
- Check if got minimum/maximum/saddle point - Note: finds LOCAL minimum
- Typically no need for explicit check (assume function does not have maxima/saddles
- Translate problem into: find $x$ such that $f(x)=0$


## Solving Non-Linear Equations - Newton Method

- Consider Taylor expansion

$$
f\left(x_{0}+\epsilon\right)=f\left(x_{0}\right)+f^{\prime}\left(x_{0}\right) \epsilon+\frac{1}{2} f^{\prime \prime}\left(x_{0}\right) \epsilon^{2}+\ldots .
$$

- Neglect terms > 1

$$
f\left(x_{0}+\epsilon\right) \approx f\left(x_{0}\right)+f^{\prime}\left(x_{0}\right) \epsilon .
$$

- In 1D
- Set $x_{0}$ - initial guess
- While $f\left(x_{i}\right)$ not 0


$$
-d x=-f\left(x_{i}\right) / f^{\prime}\left(x_{i}\right)
$$

$$
\text { - } x_{i+1}=x_{i}+d x
$$

## Newton Method in nD

- $f(x)$ vector
- $\Delta f(x)$ - matrix
- Set $x_{1}$ - initial guess
- While $\left\|f\left(x_{i}\right)\right\|>0$
- Solve $\Delta f\left(x_{i}\right) d x=-f\left(x_{i}\right)$
- Solve linear system
- $x_{i+1}=x_{i}+d x$


## Solving Linear System

- Solve $A x=B \quad$ ( $A_{n \times n}$ matrix)
- Choice I: Compute $A^{-1} \boldsymbol{O}\left(\mathbf{n}^{3}\right)$ TERRIBLY expensive
- Choice II: Iterative (Gauss/Gauss-Seidel)
- Set $x$ to initial guess
- Solve one equation at a time
- $A_{i} x=B_{i}$ - consider all $x_{j}(j \neq i)$ as constant and compute $x_{i}$ $=x_{i}=\left(b_{i}-\Sigma a_{j} x_{j}\right) / a_{i}$
- Repeat (for all i) till convergence
- Works only for a very small set of matrices


## Solving Linear System

- Choice III: LU (or LDL $^{\top}$ ) decomposition
- Compute matrices $L \& U$ such that
- $L U=A$
- L - lower matrix (has 1's on diagonal \& 0's above)
- $U$ - upper matrix (has 0 's below diagonal
- Use off-the-shelf algorithm/code
- Take advantage of sparsity (if applicable)
- Solve:
- Solve $L y=B$ (use Gauss iterations)
- Works (at each point add ONE variable)
- Solve $U x=y$ (use Gauss iterations)
- Start from $i=n-1$ and go "up"
- Works (at each point add ONE variable)

