# Approximate Implicitization using Chebyshev Polynomials 

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## Approximate Implicitization using Chebyshev Polynomials

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## Introduction

## Representation of Curves and Surfaces

- Parametric representation: Rational surface given by

$$
\mathbf{p}(s, t)=\left(p_{1}(s, t), p_{2}(s, t), p_{3}(s, t), h(s, t)\right) \quad \text { for } \quad(s, t) \in \Omega
$$

and bivariate polynomials $p 1, p 2, p 3, h$ (homogeneous form).

- Implicit (algebraic) representation: Surface given by

$$
\{(x, y, z, w): q(x, y, z, w)=0\}
$$

where $q$ is a polynomial in homogeneous form.

- For intersection algorithms it is useful to have both representations available...


## Introduction

## Motivation - Intersection Algorithms


(a) Surface-surface intersection

(b) Surface self-intersection

(c) Surface raytracing

## Implicitization

## Exact methods

- Traditional methods give exact results:
- Gröbner bases,
- Resultants and moving curves/syzygies [Sederberg, 1995],
- Linear algebra.

■ Often performed using symbolic computation.

- Surface implicitization can result in very high degrees.
- Algorithms are often slow (especially Gröbner bases).


## Implicitization

## Implicit degree of parametric surfaces



- Tensor-product bicubic patch
- 16 control points
- Total implicit degree 18
- Defined implicitly by 1330 coefficients!
- Approximation is desirable


## Implicitization

## Approximate methods

- Approximate methods where the degree $m$ can be chosen are desirable:
- keep the degree low,

■ better stability for floating pt. implementation,

- faster algorithms.
- Approximation should be good within a region of the parametric curve/surface.
- Algorithms give exact results if the degree is high enough.


## Approximate Implicitization

## Preliminaries

- First, describe implicit polynomial $q$ in a basis $\left(q_{k}\right)_{k=1}^{M}$, of degree $m$ :

$$
q(x)=\sum_{k=1}^{M} b_{k} q_{k}(x)
$$

with unknown coefficients $\mathbf{b}$.

- A good error measure is given by algebraic distance $q(\mathbf{p}(s))$.


## Approximate Implicitization

## Original method (singular value decomposition)

- Original method [Dokken, 1997], gives general framework:
- Form matrix $\mathbf{D}=\left(d_{j k}\right)_{j k=1}^{L, M}$ such that

$$
\begin{aligned}
q(\mathbf{p}(s)) & =\sum_{k=1}^{M} b_{k} q_{k}(\mathbf{p}(s)) \\
& =\sum_{k=1}^{M} b_{k} \sum_{j=1}^{L} \alpha_{j}(s) d_{j k}
\end{aligned}
$$

where $\left(\alpha_{j}\right)_{j=1}^{L}$ is a polynomial basis in $s$.

- An approximation is given by right singular vector $\mathbf{v}_{\text {min }}$ corresponding to smallest singular value of $\mathbf{D}$.


## Approximate Implicitization

## Original method

- Choosing different polynomial bases solves different approximation problems:
- Orthogonal bases solve continuous least squares problems

$$
\min _{\|\mathbf{b}\|_{2}=1} \int_{\Omega} q(\mathbf{p}(s))^{2} w(s) \mathrm{d} s
$$

- Bernstein/Lagrange bases solve problems which approximate the least squares problem.


## Approximate Implicitization

## Least squares / weak approximation

- Introduced in [Dokken, 2001], [Corless et al., 2001]:

$$
\min _{\|\mathbf{b}\|_{2}=1} \int_{\Omega} q(\mathbf{p}(s))^{2} w(s) \mathrm{d} s
$$

- Method: Form matrix $\mathrm{M}=\left(m_{k l}\right)_{k, l=1}^{M}$,

$$
m_{k l}=\int_{\Omega} q_{k}(\mathbf{p}(s)) q_{l}(\mathbf{p}(s)) w(s) \mathrm{d} s
$$

- The eigenvector corresponding to the smallest eigenvalue as the solution.


## Approximate Implicitization

## Orthogonal basis method

The original method using orthogonal polynomials can be used instead:

- Choose a basis $\left(T_{j}\right)_{j=1}^{L}$ that is orthonormal w.r.t. $w$ :

$$
\begin{aligned}
(\mathbf{M})_{k l} & =\int_{\Omega} q_{k}(\mathbf{p}(s)) q_{l}(\mathbf{p}(s)) w(s) \mathrm{d} s \\
& =\int_{\Omega}\left(\sum_{j=1}^{L} T_{j}(s) d_{j k}\right)\left(\sum_{i=1}^{L} T_{i}(s) d_{i k}\right) w(s) \mathrm{d} s \\
& =\sum_{i=1}^{L} \sum_{j=1}^{L} d_{j k} d_{i k} \int_{\Omega} T_{j}(s) T_{i}(s) w(s) \mathrm{d} s \\
& =\sum_{j=1}^{L} d_{j k} d_{j l} \\
& =\left(\mathbf{D}^{\top} \mathbf{D}\right)_{k l}
\end{aligned}
$$

## Approximate Implicitization

## Comparison of methods

- The two methods are mathematically equivalent.
- Singular values of $\mathbf{D}$ are square roots of eigenvalues of $\mathbf{D}^{T} \mathbf{D}=\mathbf{M}$, thus smallesr condition numbers for $\mathbf{D}$.
- Original method is more numerically stable.
- Original method avoids costly integration of high degree polynomials.


## Approximate Implicitization

## Why Chebyshev polynomials?

- Near equioscillating behaviour in algebraic error function.

■ Number of roots appears to correspond to convergence rates.

- Fast algorithm - based on point sampling, fast Fourier transform (FFT).
- Solves a least squares problem.
- Directly generalizable to tensor-product surfaces.


## Approximate Implicitization

## Convergence rates of approximate implicitization

| Implicit degree | 1 | 2 | 3 | 4 | 5 | 6 |
| :--- | :--- | :--- | :--- | :---: | :---: | :---: |
| Convergence rate | 2 | 5 | 9 | 14 | 20 | 27 |

Curves in $\mathbb{R}^{2}$

| Implicit degree | 1 | 2 | 3 | 4 | 5 | 6 |
| :--- | :--- | :--- | :--- | :--- | :---: | :---: |
| Convergence rate | 2 | 3 | 5 | 7 | 10 | 12 |

Surfaces in $\mathbb{R}^{3}$

- Convergence as we approximate smaller regions of the curve or surface.


## Approximate Implicitization

## Algorithm - Chebyshev method

- Generate parametric samples $\mathbf{p}_{j}=\mathbf{p}\left(t_{j}\right)$ at Chebyshev nodes $t_{j}=(\cos ((j-1) \pi /(L-1))+1) / 2$, for $j=1, \ldots, L$.
- Compute a matrix $\mathrm{D}_{0}=\left(q_{k}\left(\mathbf{p}_{j}\right)\right)_{j=1, k=1}^{L, M}$.
- Compute D by applying Discrete Cosine Transform to columns of $\mathrm{D}_{0}$ (using fast Fourier transform methods).
- Perform SVD of $\mathbf{D}\left(=\mathbf{U} \Sigma \mathbf{V}^{T}\right)$.


## Examples

## Numerical stability of weak method

- Exact implicitization of degree 5 curve using double precision:

$$
\operatorname{sing}(\mathbf{D})=\left(\begin{array}{c}
\vdots \\
2.45 \times 10^{-6} \\
6.05 \times 10^{-7} \\
3.59 \times 10^{-7} \\
4.58 \times 10^{-8} \\
1.24 \times 10^{-8} \\
6.15 \times 10^{-18}
\end{array}\right), \quad \operatorname{eig}(\mathbf{M})=\left(\begin{array}{c}
\vdots \\
6.02 \times 10^{-12} \\
3.65 \times 10^{-13} \\
1.29 \times 10^{-13} \\
2.09 \times 10^{-15} \\
1.50 \times 10^{-16} \\
6.84 \times 10^{-19}
\end{array}\right)
$$

## Examples

Newell's 32 teapot patches:

- 32 parametric patches.
- All patches are bicubic.


## Examples

Implicitization of teapot spout patches:


- Exact implicit degree 18.
- Approximated by degree 6 surfaces.
- Extra branches present.
- Can combine with other approximations to remove branches.


## Examples

## Implicitization degrees of Newells' teapot

|  | Exact $m$ | Approximate $m$ <br> 32 patches |
| :---: | :---: | :---: |
| rim | 9 | 4 |
| upper body | 9 | 3 |
| lower body | 9 | 3 |
| upper handle | 18 | 4 |
| lower handle | 18 | 4 |
| upper spout | 18 | 5 |
| lower spout | 18 | 6 |
| upper lid | 13 | 3 |
| lower lid | 9 | 4 |
| bottom | 15 | 3 |

## Examples

Implicitization of 32 teapot patches:


- 32 approximately implicitized bicubic patches.
- All patches of degree $\leq 6$.
- Extra branches present.
- No continuity conditions used.


## Examples

Implicit teapot with fewer patches:


- 26 parametric patches.
- 5 approximately implicitized patches.
- All patches of degree $\leq 6$.


## Approximate Implicitization using Linear Algebra

## Thank you!

## References:

- T. Dokken, Aspects of intersection algorithms and approximations, Ph.D. thesis, Univ. of Oslo, (1997).
- R.M. Corless et al., Numerical implicitization of parametric hypersurfaces with linear algebra, Artificial Intelligence and Symbolic Computation, Springer, (2001).


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