

Using a Multi-objective Genetic Algorithm for Curve Approximation

by Tim Sabsch, Christian Braune, <u>Alexander Dockhorn</u>, and Rudolf Kruse

Institute for Intelligent Cooperating Systems Department for Computer Science, Otto von Guericke University Magdeburg Universitaetsplatz 2, 39106 Magdeburg, Germany

Email: {tim.sabsch, christian.braune, alexander.dockhorn, rudolf.kruse}@ovgu.de



Contents

- I. Curve Fitting
- II. B-Spline Curve Fitting
- III. Multi-objective B-Spline Curve Fitting
- IV. Fitting Results
- V. Conclusion, Limitations and Future Work



Curve Fitting

- Approximate an (un-)ordered set of points / voxels with a curve
- Many algorithms require vector data such as lines, curves or surfaces
- B-splines are of special interest for applications in computer-aided geometric design
 - Their piecewise polynomial structure makes them flexible and quick to compute
 - Their structure can be easily extended to surface and hyperplanes





What do we need it for?

- This work was done to find cluster descriptors for density-based clusters.
- Those can be efficiently mined, but most prototype methods provide unsuitable approximations.
- E.g. consider the mean vector as it is commonly used for clusters found by kmeans



- Mean vector
- True approximation of the cluster form



Previous strategies – Related Work I

- Regression methods
 - Requires the order of points to be known
- Genetic algorithms have been successfully applied for the determination of optimal number and location of knots
 - Requires the order of points to be known
- Iterated Thinning / Skeleton construction / Graph construction
 - Restricted to low dimensional data
- ... or cannot fit data of certain geometric properties



Previous strategies – Related Work II

- Local Tangential Flow
 - Deals with self intersections, sharp corners and high dimensions
 - But fails in point clouds of varying density
- PCA used for ordering the points on a polynomial chain
 - Fast and deals will high dimensions and self-intersections
 - Struggles with point clouds of varying density
- Nevertheless, density based clusters need efficient descriptors as well



B-Spline Curve Fitting

• Task: find a B-spline curve that approximates the shape best

$$C(t) = \sum_{i=0}^{n} N_{i,k}(t) P_{i}$$

$$P = (P_0, P_1, \dots, P_n)$$
 is the set of control points

 $N_{i,k}(t) = (N_{0,k}(t), N_{1,k}(t), ..., N_{n,k}(t))$ is the set of B-spline basis functions defined over a degree k - 1 and a non-decreasing sequence of real numbers

$$T = (u_0, u_1, \dots, u_{n+k})$$
 is the knot vector.



B-Spline Curve Fitting

- A curve is said to be clamped uniform, if the first and last knot in the knot vector each has multiplicity *k*, and the remaining knots are evenly spaced.
 - Such a curve starts at the first control point and ends at the last control point.
- Due to the definition of the basis functions, a control point P_i only influences the curve in the interval $[u_i; u_{i+k})$ (local control property).



B-splines by example I

- P = control point
- u = knot vector
- Q = curve section





B-splines by example II

- P = control point
- u = knot vector
- Q = curve section





B-splines by example III

- P = control point
- u = knot vector
- Q = curve section
- Playing multiple control points at the same position, sharpens the curve at this section





Multi-objective Optimization with NSGA-II

- During the multi-objective optimization we want to find
 - the best fitting set of control points per b-spline
 - The best set of b-splines to approximate the dataset
- For smoothness: the curves developed in the algorithm are fixed to be cubic, i.e. of degree 3
- For control: changing a control point will only influence the curve in an interval of four knots
- The knot vector

| Parameter | Value |
|--|-------|
| Number of generations | 1000 |
| Population size | 100 |
| Crossover probability | 0.10 |
| Probability of mutating control point number | 0.01 |
| Probability of mutating control point location | 0.25 |



Objectives

- Objectives used in this study:
 - Number of control points
 - Distance minimization
 - (Length of the curve)
- Other possible objectives:
 - Near-parallel segments
 - Segments outside the points cloud
- Distance calculation:
 - Equidistant sampling of a number of points on the curve
 - Shortest distance to the target point is considered to be the distance of the curve and the point





Mutation and Crossover for B-splines

- Mutations:
 - Removing/adding a control point
 - Changing a control point via random gaussian position change

- Swapping the position of two control points
- Crossover:
 - One-point-Crossover





Results of one Pareto Front

• Models are differing in complexity and error-rate





Comparing the Results - I

- Stable results for non-intersecting point-clouds
- Even with varying density and sharp edges, no problems arise









Comparing the Results - II

- Closed forms can be approximated very well
- Few dimensions can be handled without problems
- Multiple dimensions can affect the objectives due to the curse of dimensionality







Comparing the Results - III

- Background noise can increase the complexity of the resulting model
- Dense areas will be fitted very well, whereas sparse areas are only fitted approximately





Comparing the Results - III

- Intersection can be succesfully modeled
- Nevertheless it becomes exceedingly hard to choose the best fitting model in this case.





Comparing the Results - III

- Intersection can be succesfully modeled
- Nevertheless it becomes exceedingly hard to choose the best fitting model in this case.





Comparing the Results - IV

• Sum of squared errors per algorithm on the presented datasets

| Data Set | EA-Fit | PCA-Fit |
|------------------------|--------|---------|
| Open Point Cloud | 0.4314 | 0.4806 |
| Closed Point Cloud | 0.4744 | 1.3197 |
| Varying Density | 0.2500 | 0.3617 |
| Sharp Corners | 0.0577 | 6.0421 |
| Self-Intersections | 0.6195 | 53.5088 |
| Three-Dimensional Data | 0.6819 | 1.1549 |
| Background Noise | 0.8018 | 2.5212 |



Conclusions

• A survey of existing research revealed that many publications deal with the problem of approximation, but often struggle with point clouds of high dimensions or specific geometric characteristics.

- Two properties of fitting curves were defined as objective functions for the evolutionary algorithm: the distance to the point cloud as well as the number of control points to preserve simplicity
- based on the multi-objective genetic algorithm NSGA-II
- Critical characteristics, such as non-uniform noise, sharp corners and selfintersections as well as higher dimensional data was fitted properly



Limitations and Future Work

- optimization process is constrained to the control point vector
 - Include the knot vector as well
- The best individual is currently chosen by hand or by the average rating
 - study the influence of each criterion and find better weights thereby
 - Find a method to receive the most suitable individual in the pareto-front
- For a higher number of objectives, one should consider using a Many-Objective Genetic Algorithm, such as NSGA-III
- b-splines cannot represent simple curves like circles and ellipses
 - Adapt the system to non-uniform rational b-splines (NURBS)



Thank you for your attention!

by Tim Sabsch, Christian Braune, <u>Alexander Dockhorn</u>, and Rudolf Kruse

Institute for Intelligent Cooperating Systems Department for Computer Science, Otto von Guericke University Magdeburg Universitaetsplatz 2, 39106 Magdeburg, Germany

Email: {tim.sabsch, christian.braune, alexander.dockhorn, rudolf.kruse}@ovgu.de