# Bavarian Graduate School of Computational Engineering
# Honours project

Technische Universität München

BGCE Honours project report

## CAD-integrated topology optimization


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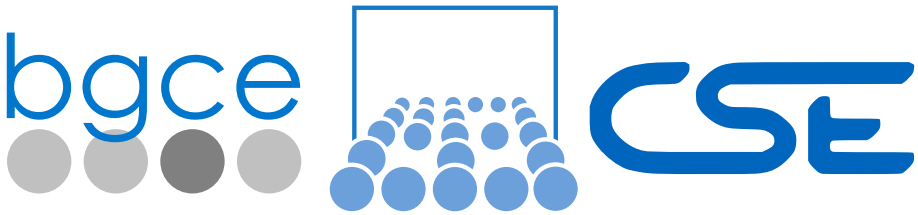


# Preface

This work evolved in the course of the software project for the BGCE class of 2016. BGCE- Who we are...

# Acknowledgments

If someone contributed to the thesis... might be good to thank them here.

# Contents

# Outline and Overview

## Purpose of the document

## Document overview

### Part I: Introduction and Theory

CHAPTER 1: INTRODUCTION

This chapter presents an overview of the thesis and it purpose. Furthermore, it will discuss the sense of life in a very general approach.

CHAPTER 2: THEORY

No thesis without theory.

### Part II: The Real Work

CHAPTER 3: OVERVIEW

This chapter presents the requirements for the process.

# Part I.

# Introduction

# 1. Introduction

BGCE - who are we? moved to preface

## 1.1. Motivation

## 1.2. Important concepts

### 1.2.1. Computer Aided Design - CAD

### 1.2.2. Topology Optimisation

## 1.3. Project structure

### 1.3.1. Aims and Goals

### 1.3.2. Timeline and Structure

## 1.4. Acknowledgement of supervisors

# Part II.

# Background Theory

# 2. Background Theory

## 2.1. CAD in computers

### 2.1.1. History of CAD

Computer aided design (short: CAD) refers to the process of designing a product using a computer system. Before CAD applications were used, products were constructed using a sketch board. It was a challenge to incorporate changes in the construction drafts as well as to keep documentations up to date; hence, it was no surprise that CAD systems spread rapidly across all design development branches. Computer aided design is now irreplaceable used in architecture, mechanical, electrical and civil engineering.

Depending on the discipline different requirements are set on the virtual model. One may imagine that in a civil engineering model of a building a 2D floor plan is often sufficient; however in the design of a mechanical motor a 3D model is always necessary. Given these circumstances, various CAD software bundles evolved in the different disciplines with completely different modelling approaches. Besides the geometry representation parameters, such as material properties or manufacturing information, are stored. In order to move between different data structures standardized exchange interfaces are commonly used.

### 2.1.2. Geometry representations

In general, two different ways of describing a geometry are used in CAD systems: constructive solid geometry consisting of a set of primitive forms or storing the boundary of a part assuming that the interior is filled (BREP). Other approaches, such as a complete voxelised geometry are not common due to extensive memory consumption.

#### Constructive solid geometry

insert figure csg tree from wikimedia
One way of representing a geometry in CAD is the approach of *constructive solid geometry* (short: CSG). The basic idea is to start from a set of primitives, e.g. a sphere, cylinder and cube. Basic Boolean operations link these primitives towards a complex geometry.

Key advantages of this format is the precise representation using very few storage memory. However, not all desired forms can be represented by CSG and hence, a second type of geometry description is needed.

#### Boundary representation

A different kind of modelling approach is the so-called *boundary representation*. Instead of storing the geometry information at every single point, *BREP* formats only save the

boundary surface of the body. The interior is assumed to be uniformly filled. Especially in big geometries this approach simplifies the model immensely to an extend that amounts of data are better to handle. Surfaces can be stored as tetrahedrons (see later STL files) or in NURBS patches. Furthermore, holes in the body are possible by saving the surface normal of the boundary surface.

By the boundary representation arbitrary geometries can be created. Data amounts to fulfill a certain precision are larger than by the csg representation, but BREP files are usually easier to work with. Beware, that unreal geometries can be created using BREP formats.

### 2.1.3. Data exchange file formats

## 2.2. Topology Optimisation

### 2.2.1. Definition and motivation

Topology Optimization describes the process of finding the optimal distribution of a limited amount of material for a given area or volume based on a predefined constraint/minimization problem. Possible optimization goals are for example:

- **Minimum compliance** which seeks to find the optimal distribution of material that returns the stiffest possible structure. The structure is thereby subjected to loads (forces) and supports (boundary conditions). By maximizing the stiffness, we minimize the compliance.

- **Heat conduction** tries to optimize the domain of a conductive material with respect to conductivity for the purpose of heat transfer. This maximization problem is the same as minimizing the temperature gradient over the domain– a poor conductor will create a large gradient.

- **Mechanism synthesis**' objective is to obtain a device that can convert an input displacement in one location to an output displacement in another location. Topology Optimization hereby seeks the optimal design which maximizes the output force for a given input or, respectively, minimizes the input force for a given output.

As one can imagine by this short list of optimization goals, Topology Optimization has a wide field of possible applications. Hence, it has become a well established technology used by engineers in the fields of aeronautics, civil, materials, mechanical and structural optimization. Furthermore, the rising significance of 3D-printers in industry, the realisation of computed optimized designs is now much easier.

### 2.2.2. Theory

### 2.2.3. ToPy

ToPy [2] is a python library/program, written by William Hunter and documented in [1]. It is based on the 99-line Matlab code by Sigmund's for minimum compliance. The program

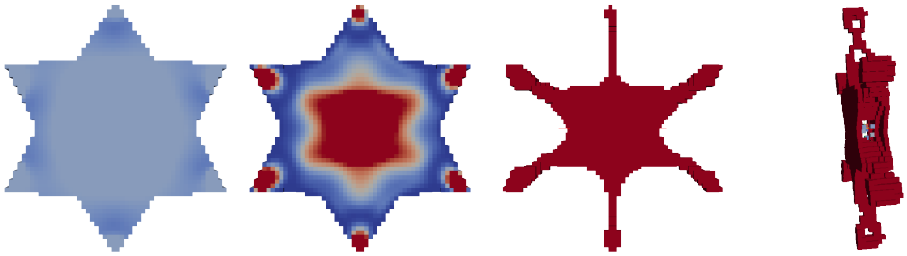


Figure 2.1.: Topology Optimization with minimum compliance of a star structure, given by an stl-file. The fixtures were applied in the corners of the star, while a load was set in the middle.

can optimize the three above named problem types, minimum compliance, heat conduction and mechanism synthesis– in 2D as well as 3D. It uses available open source python software, as for example Pysparse and Numpy, leading to improved speed, porta- and scalability. The whole program is steered by an input file which– with the help of the documentation– is straightforward to use and easy to adapt.

### 2.2.4. Implementation

In terms of our implementation, we use ToPy as a blackbox topology optimizer. This means, we launch the program with an input file based on our scenario, let ToPy run and proceed by working with the output of ToPy. The intention is to touch the solver itself as less as possible to be able to just plug in different solvers later on. Implementation-wise that means, that we wrote a program which takes as input a voxelized CAD design in, for example, stl-format and outputs a tpd-file which can be used by ToPy. Results of the process can be seen in figure 2.1. Here, a star was given as input from a stl-file. We fixed the voxels in the corners of the structure, while we set a load in the middle, pointing into the structure. As can be seen, the optimization process ”cuts” away unnecessary material in-between the corners and even in the middle of the material and returns stiff structure for a minimal amount of material. (maybe a bit wishy washy here)

## 2.3. From CAD to Voxels

## 2.4. From Voxels to a surface representation

### 2.4.1. Isosurface Contouring

Now when the optimized voxel data was obtained, the next step is to generate a *mesh based geometry*. It will be useful in the further NURBS implementation. In order to achieve it, the data will be represented by a contour of a smooth function, rendering an isosurface. The isosurface allows to visualize Scalar Volumetric Data in 3D. It furthermore permits a mesh representation of the volume data. The mesh can be composed of triangles or quads,

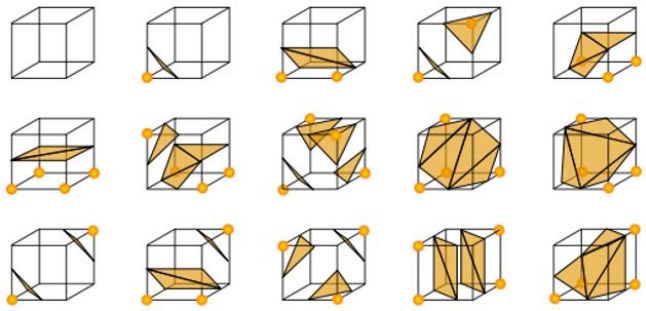


Figure 2.2.: Basis cases of Marching Cubes

according to the algorithm used. There are two main approaches to solve this problem, the most famous one is Marching Cubes.

### Marching Cubes

This algorithm takes as an input a regular volumetric data set and extracts a polygonal mesh. It divides the space into cubes, which are defined by the volume information. Each cube has scalar information on its vertices, the value is equal or above a marked isovalue. Therefore each of the eight vertices of a cube can be marked or unmarked. According to these values vertices are drawn on the edges of the cube at calculated points with the use of interpolation. A cube that contains an edge is called active. Non active cubes are not further considered in the algorithm.

By connecting the vertices we obtain a polygon on each cube. There are 256 possible scenarios, but most of them are just reflections or rotationally symmetric cases of each other. Therefore there are 15 base cases which represent all the possibilities of the marching cubes (Figure 2.1). The original algorithm presents two main problems. Firstly it does not guarantee neither correctness nor topological consistency, which means that holes may appear on the surface due to inaccurate base case selection. The second problem is ambiguity, which appears when two base cases are possible and the algorithm chooses the incorrect one. These cases can be grouped into face ambiguities and internal ambiguities. There are many extended Marching Cubes algorithms that tackle the problems of the original one, getting rid of the ambiguities and providing correctness.

### Dual Contouring

The idea of this algorithm is similar to Marching Cubes, but instead of generating vertices on the edges of the cubes, it locates them inside the cube. Figure 2.5 shows the basic differences in both approaches. The vertices associated with the four contigous cubes are joined and form a quad. The question now is which place inside the cube is the ideal one to insert each vertex. Different dual algorithms are classified according to the answer for this question. Dual contouring generates a vertex positioned at the minimizer of a quadratic function which depends on the intersection points and normals. Therefore the method needs Hermite data to work with.

$$E(x) = x^T A^T A x - 2x^T A^T b + b^T b$$

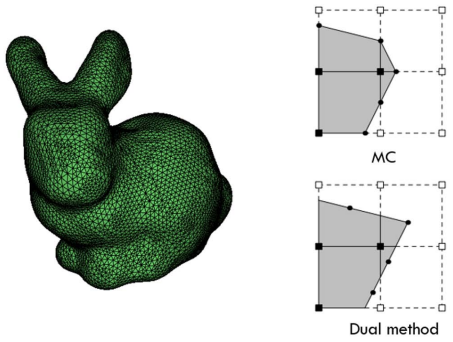



Figure 2.3.: *Right:* The famous Standford Bunny. *Left:* Main difference between MC and Dual methods

Where $A$ is a matrix whose rows are the normals and $b$ is a vector whose entries are the product of normals and intersection points. To solve this system, a nummerical treatement is needed. As proposed in [1] the best approach is to compute the SVD decomposition of $A$ and form the pseudo-inverse by truncating its small singular values.

The main advantage of this method over MC is the adquisition of better aspect ratios. On the other hand the need of Hermite Data represents a disadvantage. Furthermore there is no open source algorithm that implements the Dual Contouring scheme.

### 2.4.2. The VTK Toolbox

#### Installing VTK

VTK was installed using the Linux platform, for it to be successfully implemented a gcc compiler must be already on the machine. VTK offers the possibility to use Python, TLC or C++ for development. VTK toolbox is actually a C++ library, which is implemented in other languages. We decided to continue the project with C++ since it gives the possibility to explore the original code. A few dependency problems were encountered, nevertheless they were easy to track back. If any problems were to be found at installation time, please refer to the VTK Wiki where the procedure is explained step by step.

#### Implementing the VTK Classes

The VTK toolbox was used in order to implement the algorithms on our optimized data. It is a heavily object oriented toolbox. Our first approach was to use the built in Marching Cubes algorithm, nevertheless it did not work with our unstructured grid data. It just works for ImageData and PolyData . For structured and unstructured grids the tool to render the isosurface is the contour Filter tool. Unfortunately the documentation does not present which algorithm the tool uses. It can be inferred that it is an extended Marching cube algorithm.

The Contour Filtering seemed to work fine but the visualization of our data was still not possible and an intermediate step was needed. We used the Implicit Modelling tool which is a filter that computes the distance from the input geometry to the points of an output

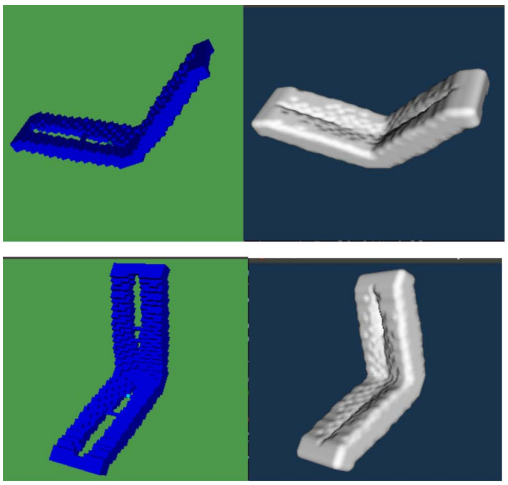


Figure 2.4.: Contour Filtering tool after Implicit Modelling

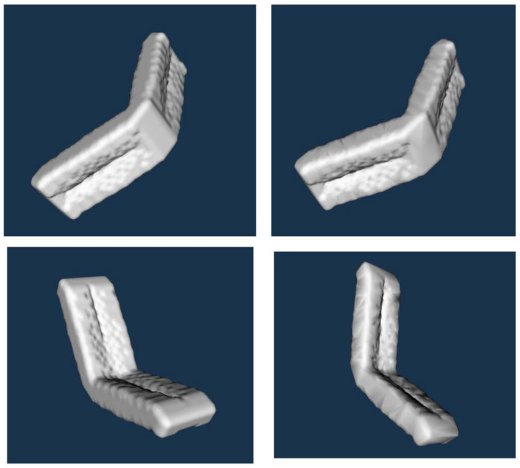


Figure 2.5.: Decimation of triangles. *Top:* 50% *Lower:*90%

structured point set. This distance function can then be "contoured" to generate new, offset surfaces from the original geometry. It finally allowed visualization but it created one problem. Holes are lost in the process.

A further idea to solve this problem is to convert at the first step the volume data into point data and only then present it to the Contour Filtering Tool. This will be implemented in the next milestone.

The next step was to create a coarser mesh from the fine one. The triangles that represent the isosurface can be reduced with the Decimation tool. A smoothing step is necessary in between to get the new connections right. The top part of figure [2] shows a 50 % reduction of the triangles, a noticeable difference can not be perceived. On the lower part a 90 % reduction is obtained, it is nevertheless still difficult to see a difference. Triangle meshes can be easily coarsened since there are many open source algorithms that simplify the triangles. VTK has the decimation tool which works for 3D triangle data.

### 2.4.3. The Long Road to NURBS

There are two possible roads to go from the voxel data to the NURBS representation.

#### Quad Contouring

This approach uses the dual contouring algorithm as first step in order to obtain a quad mesh representation from the voxel data. The first challenge is to implement correctly the algorithm with the ideas presented in [1]. The original marching cubes algorithm is implemented in VTK but the source code is not public, therefore not only an extension of it is needed, but a full implementation. Once this first step is done, the quads will be chosen for the NURBS parametrization. A second step considers multiple smaller quads which have to be combined into one larger patch. This is another challenge, since the remeshing of quad meshes is not as straight forward as with the triangles. Different approaches have been taken in order to achieve this coarsening. In [2] an incremental and greedy approach, which is based on local operations only, is presented. It depicts an iterative process which performs local optimizing, coarsening and smoothing operations. Another approaches, like the one presented in [3] uses smooth harmonic scalar fields to simplify the mesh.

#### Multiresolution Analysis of Arbitrary Meshes

With this approach there is no need to apply a Dual Contouring algorithm, since it takes as beginning data the triangles from the Marching Cubes. The main concepts are shown in the paper of the same name [4]. It mainly takes a series of intermediate steps which permits a parametrization of data. It includes a partitioning scheme based on the ideas of the Voronoi Diagrams and Delaunay triangulations. Large patches or quads are obtained with this method. Further discussion on this approach is explained in the following section.

Both approaches have not been implemented in open source documentation, therefore it will be a long road to achieve what is required. For the first part the second road was chosen and in case it leads to a dead end, the first way will be taken into consideration.

## 2.5. From a surface representation to NURBS

### 2.5.1. Bezier Curves

*Bezier curve* is a *parametric* curve, which often used for producing a smooth approximation of a given set of data points.

#### Analytical expression

An analytical expression for the Bezier curve is given by:

$$\vec{B}(t) = \sum_{i=0}^{n} b_i^n(t)\vec{P}_i,$$

where $\vec{P}_i$ is the $i$–th control point (we have $n+1$ control points). And

$$b_i^n(t) = \begin{pmatrix} n \\ i \end{pmatrix} (1-t)^{(n-i)} t^i$$

is the $i$–th Bernstein polynomial of degree $n$.

Additionally to the expression with the Bernstein polynomials, one can use a recursion formula (**de Casteljau Algorithm**) for the construction of the Bezier–curve, which we will not cover here.

#### Surfaces

Analogically to Beziercurves, but with $n \cdot m$ Points $\vec{P}_{i,j}$ and the analytical expression

$$\vec{S}(u,v) = \sum_{i=0}^{n} \sum_{j=0}^{m} b_i^n(u) b_j^m(v) \vec{P}_{i,j}$$

one can define a *Bezier surface*

> Bezier–curves and surfaces may be unstable! Minor changes in control points might lead to major global changes!

### 2.5.2. NURBS basis functions

Extending the idea, described in previous section, one could use NURBS basis functions instead of simple Bezier curves.

Unlike Bezier curves, for the B-spline basis a parameter domain is subdivided with, so-called, *knots*. In particular, given the parameter domain $[u_0, u_m]$ (in 1D), *knot vector* is given by $u_0 \leq u_1 \leq ... \leq u_m$. In most cases $u_0 = 0, u_m = 1$, so we get unit interval for our parameter values. Recall, that, N in NURBS stands for *non-uniform*. This means, that our knots $u_0, ..., u_m$ are not equidistant.

Given *knot vector* $[u_0, u_m]$ and a degree of B-spline $p$ one can find $i$-th B-spline basis function recursively as follows:

$$N_{i,0}(u) = \begin{cases} 1, & \text{if } u_i \leq u < u_{i+1} \\ 0, & \text{otherwise} \end{cases} \tag{2.1}$$

$$N_{i,p}(u) = \frac{u - u_i}{u_{i+p} - u_i} N_{i,p-1}(u) + \frac{u_{i+p+1} - u}{u_{i+p+1} - u_{i+1}} N_{i+1,p-1}(u) \tag{2.2}$$

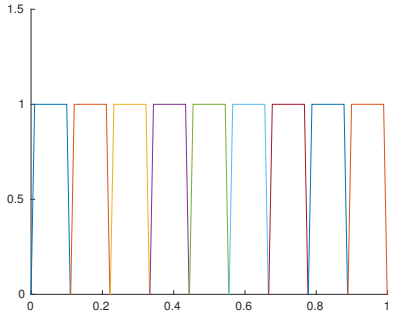
For $p = 0$ we get just step functions (see fig. 2.5.2), for $p = 1$ we get familiar hat functions (see fig. 2.5.2). Quadratic basis looks a bit more complicated, but also quite intuitive (fig. 2.5.2).

Given these basis functions, Non-Uniform Rational B-Spline curve is given by:

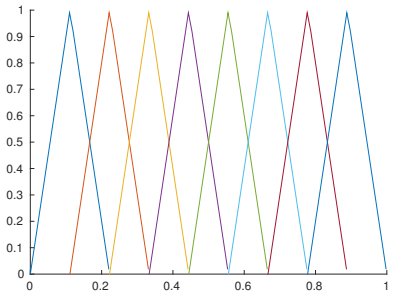
$$C(u) = \frac{\sum_{i=1}^{k} N_{i,n} \omega_i P_i}{\sum_{i=1}^{k} N_{i,n} \omega_i}, \tag{2.3}$$

where $k$ is number of points, $\{P_i\}$ are given control points.

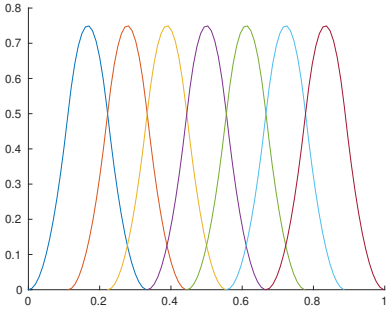
B–splines are have the following properties, which are useful for our problem:




(a) B-spline basis for $p = 0$




(b) B-spline basis for $p = 1$




(c) B-spline basis for $p = 2$

Figure 2.6.: B-spline basis functions

- degree $n$ and number of control points $\vec{P}_{i\cdots m}$ are independent!
- B–Splines only change locally (depends on the degree $n$) when a control point is changed.

Analogically, one can define B–spline surfaces.

### 2.5.3. Minimization problem

Now, once we defined all necessary tools, we proceed to the fitting problem.

**The goal:** Fit in a parametric curve to the set of given data points.

In our case our given set of points is a mesh, obtained on a previous step.

### 2.5.4. Minimization Problem: Bezier curve

First we want to find a Bezier–curve $\vec{B}_n(t)$ of degree $n$ which is approximating a given spline $\vec{s}_m(t)$ defined by $m$ points in a optimal way. For this purpose we want to minimize the L2–error. This leads to the minimization problem:

$$\text{find} \min_{\vec{B}_n \in \mathbb{B}_n} \left\| \vec{B}_n - \vec{s}_m \right\|_{L_2} \tag{2.4}$$

The function space $\mathbb{B}_n$ is composed of functions of the following form:

$$\vec{B}_n(t) = \sum_{i=0}^{n} a_{2i} \begin{pmatrix} b_i^n(t) \\ 0 \end{pmatrix} + a_{2i+1} \begin{pmatrix} 0 \\ b_i^n(t) \end{pmatrix} \tag{2.5}$$

Therefore a control point for the Bezier–curve has the following form:

$$\vec{P}_i = \begin{pmatrix} a_{2i} \\ a_{2i+1} \end{pmatrix}. \tag{2.6}$$

Minimizing the L2–norm is equal to minimizing the functional:

$$F(\vec{B}_n) = \int_{t=0}^{t=1} \left( \vec{B}_n - \vec{s}_m \right)^2 \mathrm{dt} \tag{2.7}$$

Varying $B_n$ yields

$$\delta F(B_n) = 2 \int_{t=0}^{t=1} \left( \vec{B}_n - \vec{s}_m \right)^T \delta \vec{B}_n \mathrm{dt} \tag{2.8}$$

using the definition of $\vec{B}_n$ and $\delta \vec{B}_n$

$$\vec{B}_n(t) = \sum_{i=0}^{n} a_{2i} \begin{pmatrix} b_i^n(t) \\ 0 \end{pmatrix} + a_{2i+1} \begin{pmatrix} 0 \\ b_i^n(t) \end{pmatrix} \tag{2.9}$$

$$\delta \vec{B}_n(t) = \sum_{i=0}^{n} \delta a_{2i} \begin{pmatrix} b_i^n(t) \\ 0 \end{pmatrix} + \delta a_{2i+1} \begin{pmatrix} 0 \\ b_i^n(t) \end{pmatrix} \tag{2.10}$$

leads to

$$\delta F(B_n) = 2 \int_{t=0}^{t=1} \left( \sum_{i=0}^{n} a_{2i} \begin{pmatrix} b_i^n(t) \\ 0 \end{pmatrix} + a_{2i+1} \begin{pmatrix} 0 \\ b_i^n(t) \end{pmatrix} - \vec{s}_m \right)^T \left( \sum_{j=0}^{n} \delta a_{2j} \begin{pmatrix} b_j^n(t) \\ 0 \end{pmatrix} + \delta a_{2j+1} \begin{pmatrix} 0 \\ b_j^n(t) \end{pmatrix} \right) \mathrm{dt} \stackrel{!}{=} 0 \quad (2.11)$$

rewritten

$$\int_{t=0}^{t=1} \left( \sum_{i=0}^{n} a_{2i} \begin{pmatrix} b_i^n(t) \\ 0 \end{pmatrix} + a_{2i+1} \begin{pmatrix} 0 \\ b_i^n(t) \end{pmatrix} \right)^T \left( \sum_{j=0}^{n} \delta a_{2j} \begin{pmatrix} b_j^n(t) \\ 0 \end{pmatrix} + \delta a_{2j+1} \begin{pmatrix} 0 \\ b_j^n(t) \end{pmatrix} \right) \mathrm{dt} = \int_{t=0}^{t=1} \vec{s}_m^T \left( \sum_{j=0}^{n} \delta a_{2j} \begin{pmatrix} b_j^n(t) \\ 0 \end{pmatrix} + \delta a_{2j+1} \begin{pmatrix} 0 \\ b_j^n(t) \end{pmatrix} \right) \mathrm{dt} \quad (2.12)$$

or using the notation

$$\phi_{2i} = \begin{pmatrix} b_i^n(t) \\ 0 \end{pmatrix} \quad (2.13)$$

$$\phi_{2i+1} = \begin{pmatrix} 0 \\ b_i^n(t) \end{pmatrix} \quad (2.14)$$

we get

$$\int_{t=0}^{t=1} \left( \sum_{i=0}^{2n+1} a_i \phi_i \right)^T \left( \sum_{j=0}^{2n+1} \delta a_j \phi_j \right) \mathrm{dt} = \int_{t=0}^{t=1} \vec{s}_m^T \left( \sum_{j=0}^{2n+1} \delta a_j \phi_j \right) \mathrm{dt} \quad (2.15)$$

or

$$\sum_{i=0}^{2n+1} \sum_{j=0}^{2n+1} a_i \delta a_j \int_{t=0}^{t=1} \phi_i^T \phi_j \mathrm{dt} = \sum_{j=0}^{2n+1} \delta a_j \int_{t=0}^{t=1} \vec{s}_m^T \phi_j \mathrm{dt} \quad (2.16)$$

this has to be true for any $j$ and $\delta a_j$, therefore

$$\sum_{i=0}^{2n+1} a_i \int_{t=0}^{t=1} \phi_i^T \phi_j \mathrm{dt} = \int_{t=0}^{t=1} \vec{s}_m^T \phi_j \mathrm{dt} \; \forall j = 0 \cdots 2n+1 \quad (2.17)$$

using

$$A_{ij} = \int_{t=0}^{t=1} \phi_i^T \phi_j \mathrm{dt} \text{ and } b_j = \int_{t=0}^{t=1} \vec{s}_m^T \phi_j \mathrm{dt} \quad (2.18)$$

we get the linear equation system

$$Aa = b \quad (2.19)$$

which has to be solved for $a$.

### 2.5.5. Minimization problem(least squares): NURBS

Although the approach used above showed good results, it appears to be very computationally extensive. Analogically, one could reduce the original problem to the *linear regression problem*, which allows us to reduce computational costs. Also, to improve the locality of our solution, from now on we are going to use NURBS basis functions with weights $\omega_j = 1$ instead of Bezier curves.

Let $X^0$ be the $n \times 2$ matrix of the given set of points, $N^p$ - the basis functions of degree $p$ ($n \times (n+p)$ matrix, where $n$ - number of points), $P^0$ - the control points ($(n+p) \times 2$ matrix).

The original problem can be written as:

$$X_i^0 = \sum_{j=1}^{n+p} P_j^0 N_{i,j}^p, \quad i \in \{1, .., n\} \tag{2.20}$$

Or, in short:

$$X^0 = N^p P^0 \tag{2.21}$$

The above system needs to be solved for the unknown $P^0$. One of the ways to solve it is to use SVD decomposition. So far, we used built-in MATLAB solver.

### 2.5.6. Reparametrization

In our simple case we use coordinates of our points as a parameters, but even more advanced parametrization algorithms usually don't give an optimal parametrization. For handling this issue in (reference!!!) the following iterative algorithm was proposed:

1. *Fitting step:* For **fixed parametrizations** $\{t_i\}$ , the optimal control points are found by solving a linear least-squares problem.
2. *Parameter correction step:* For **fixed control points**, optimal parametrizations $\{t_i\}$ are found by projecting the points onto our surface.

The first part of the algorithm is exactly the problem we described in a previous section. The second part can be tackled by solving linearised system of equations, which provide us relatively cheap (we need to solve only a system of linear equations) and good (see fig. ) method for the parameter correction.

### 2.5.7. Fitting pipeline

Since the geometry obtained after topology optimization can be arbitrary complex, we might not be able to find a food fit using only one patch. We seek a multi step algorithm, allowing us to break the overall big problem into smaller problems, which can be handled relatively easy. Based on the algorithm described in (reference to ...), our overall fitting pipeline looks as follows (see fig. 2.7):

- Patch selection (breaking our problem in small pieces which can be solved using least squares)
- Parametrization of obtained patches

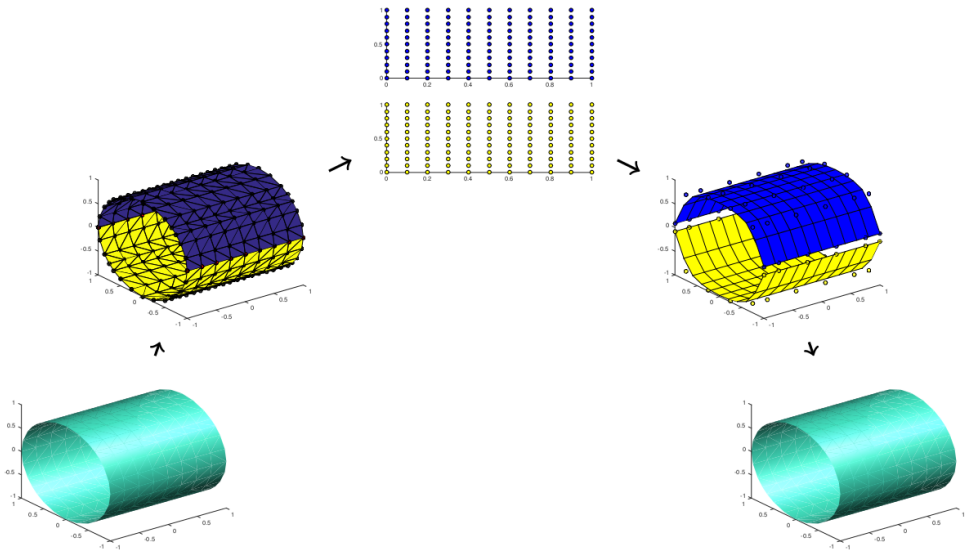


Figure 2.7.: Fitting pipeline

- B–spline fitting using least squares
- Smooth connection of patches
- Conversion back to CAD

# Appendix

# A. Detailed Descriptions

Here come the details that are not supposed to be in the regular text.

# Bibliography

[1] William Hunter. Predominantly solid-void three-dimensional topology optimisation using open source software. Master's thesis, Stellenbosch University, 2009.

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