

Computer Aided Geometric Design

Surface Representations

©Gershon Elber, Technion

based on a book by Cohen, Riesenfeld, & Elber

Tensor Product Surfaces

Definition 13.1:

Consider F and G , two sets of univariate functions with intervals domains U and V , respectively,

$$F = \{ f_i(u) \}_{i=0, m}, \quad G = \{ g_j(v) \}_{j=0, n}.$$

A surface formed by

$$h(u, v) = \sum_{j=0}^n \sum_{i=0}^m c_{i,j} f_i(u) g_j(v)$$

is called a tensor product surface with domain $U \times V$.

If $c_{i,j} \in R^3$ for all i, j , then h is a parametric surface.

A Bilinear Surface



Example 13.2:

Consider the linear blending functions

$F = \{ f_0(u) = 1-u, f_1(u) = u \}$ and $G = \{ g_0(v) = 1-v, g_1(v) = v \}$,
with domain $U = [0, 1]$ and $V = [0, 1]$. The tensor product surface

$$\begin{aligned} h(u, v) = & c_{0,0} f_0(u) g_0(v) + c_{0,1} f_0(u) g_1(v) \\ & + c_{1,0} f_1(u) g_0(v) + c_{1,1} f_1(u) g_1(v) \end{aligned}$$

is a bilinear tensor product surface with domain $U \times V$.

Question: What is the value of $h(u, v)$ at $u = 0, 1$ and $v = 0, 1$?

A Tensor Product Bezier Surface

Definition 13.3:

Consider $\mathbf{P} = \{ P_{i,j} \in \mathbb{R}^3 \mid 0 \leq i \leq m, 0 \leq j \leq n \}$ and collection of functions $\mathbf{F} = \{ \theta_{i,m}(u) \}_{i=0}^m$ $\mathbf{G} = \{ \theta_{j,n}(v) \}_{j=0}^n$.

The parametric surface

$$\sigma(u, v) = \sum_{j=0}^n \sum_{i=0}^m P_{i,j} \theta_{i,m}(u) \theta_{j,n}(v)$$

is called a degree $m \times n$ tensor product Bezier surface with domain $U \times V = [0, 1] \times [0, 1]$.

Question: What is the value of $\sigma(u, v)$ at $u = 0, 1$ or $v = 0, 1$?

Bezier Surfaces (Cont.)

From properties of Bernstein polynomials

$$\sigma(u,0) = \sum_{j=0}^n \sum_{i=0}^m P_{i,j} \theta_{i,m}(u) \theta_{j,n}(0) = \sum_{i=0}^m P_{i,0} \theta_{i,m}(u),$$

$$\sigma(u,1) = \sum_{j=0}^n \sum_{i=0}^m P_{i,j} \theta_{i,m}(u) \theta_{j,n}(1) = \sum_{i=0}^m P_{i,n} \theta_{i,m}(u),$$

$$\sigma(0,v) = \sum_{j=0}^n \sum_{i=0}^m P_{i,j} \theta_{i,m}(0) \theta_{j,n}(v) = \sum_{j=0}^n P_{0,j} \theta_{j,n}(v),$$

$$\sigma(1,v) = \sum_{j=0}^n \sum_{i=0}^m P_{i,j} \theta_{i,m}(1) \theta_{j,n}(v) = \sum_{j=0}^n P_{m,j} \theta_{j,n}(v).$$

A Tensor Product B-spline Surface

Definition 13.4:

Consider $\mathbf{P} = \{ P_{i,j} \in R^3 \mid 0 \leq i \leq m, 0 \leq j \leq n \}$ and collection of functions $F = \{ B_{i,k_u,\tau_u}(u) \}_{i=0}^m$, $G = \{ B_{j,k_v,\tau_v}(v) \}_{j=0}^n$, where τ_u and τ_v are knot vectors of length $m + k_u + 2$ and $n + k_v + 2$, respectively.

The parametric surface

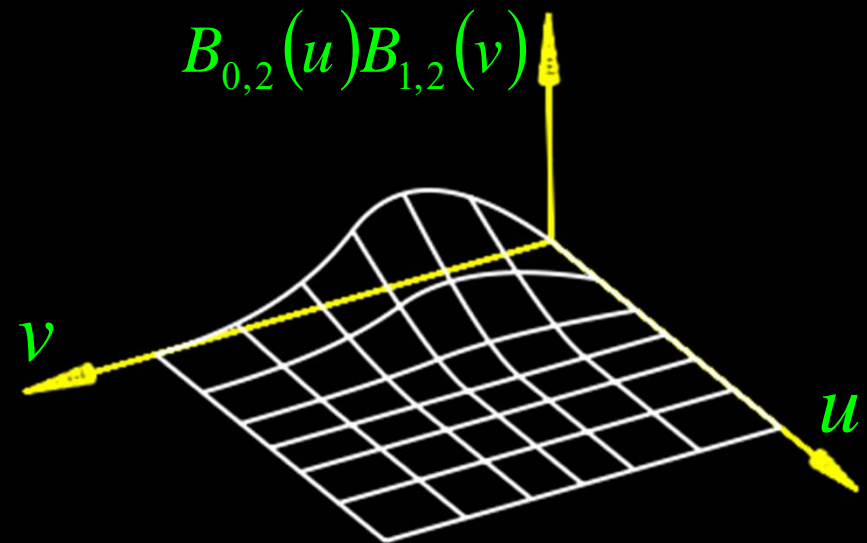
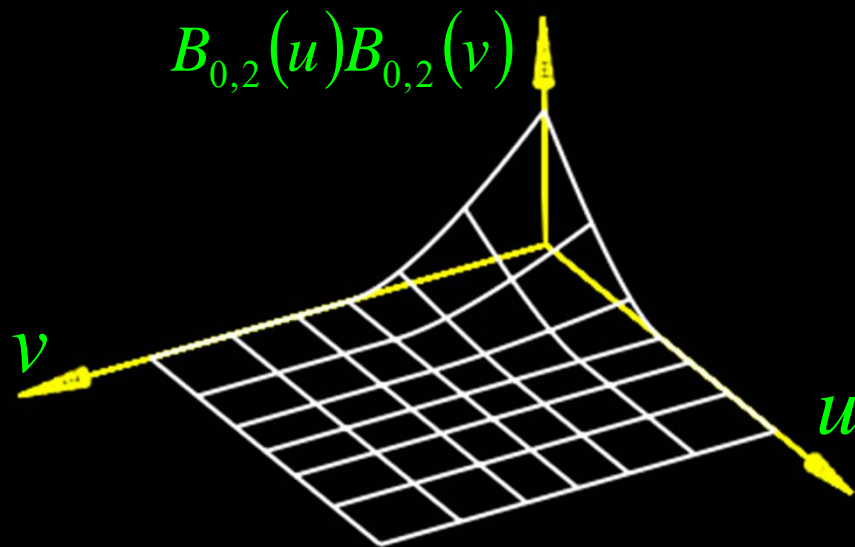
$$\sigma(u,v) = \sum_{j=0}^n \sum_{i=0}^m P_{i,j} B_{i,k_u,\tau_u}(u) B_{j,k_v,\tau_v}(v)$$

is called a degree $k_u \times k_v$ tensor product B-spline surface with domain

$$U \times V = [\tau_u(k_u), \tau_u(m+1)] \times [\tau_v(k_v), \tau_v(n+1)].$$

B-spline Products

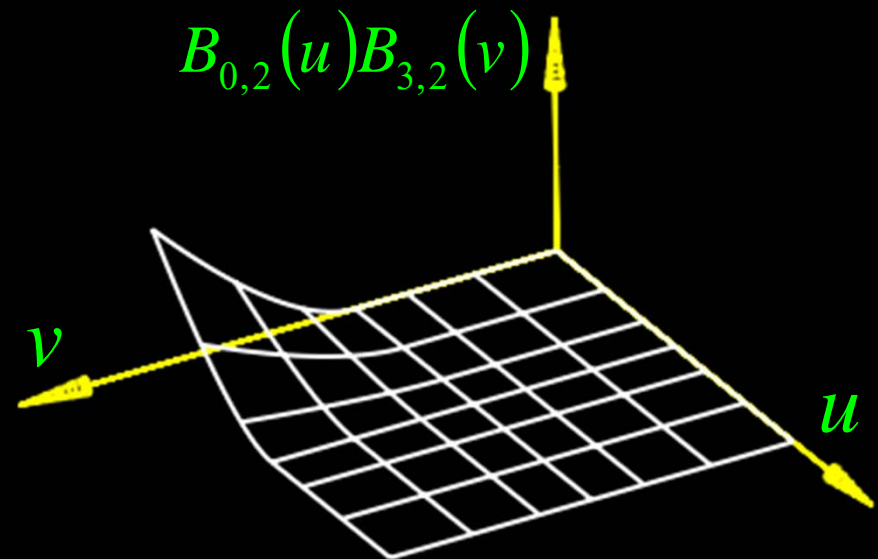
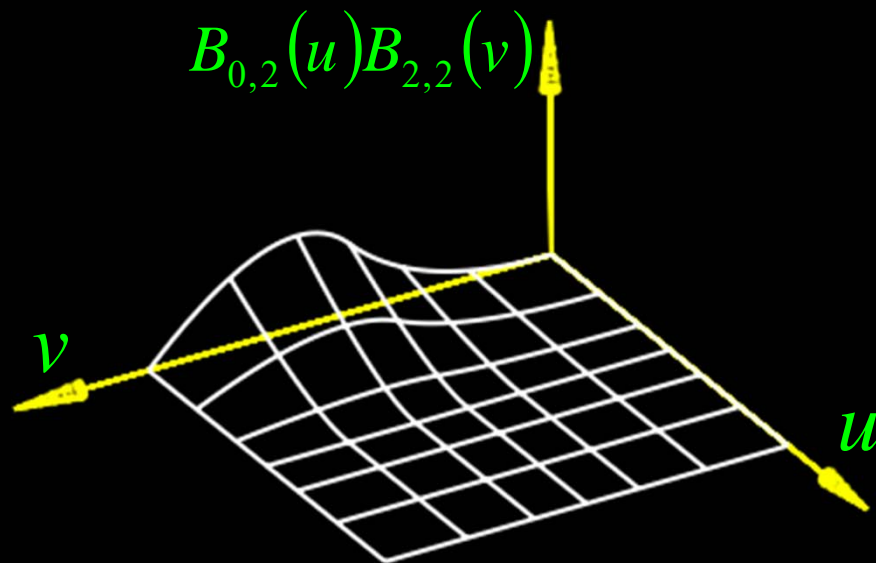
Example 13.5: Consider $\tau_u = \tau_v = \{0, 0, 0, 1, 2, 2, 2\}$ and quadratic functions. We draw the different products:



B-spline Products (Cont.)

Example 13.5 (Cont.):

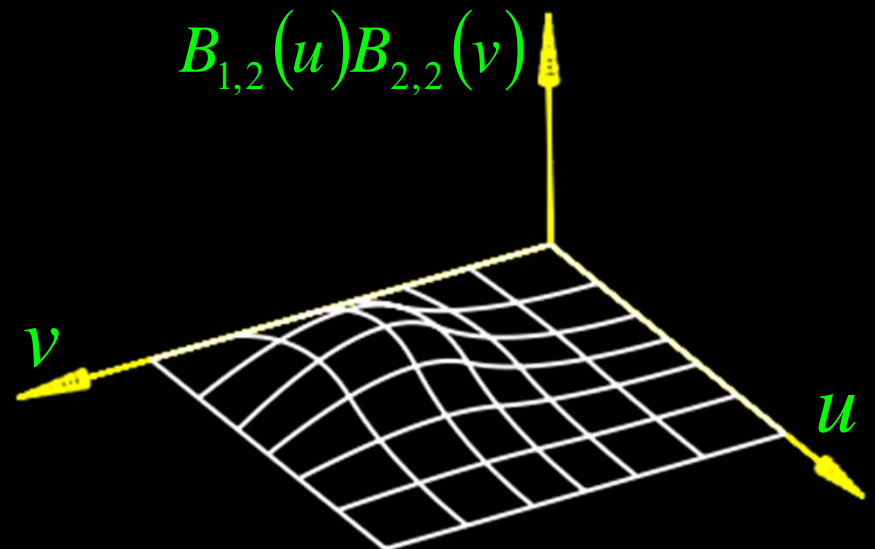
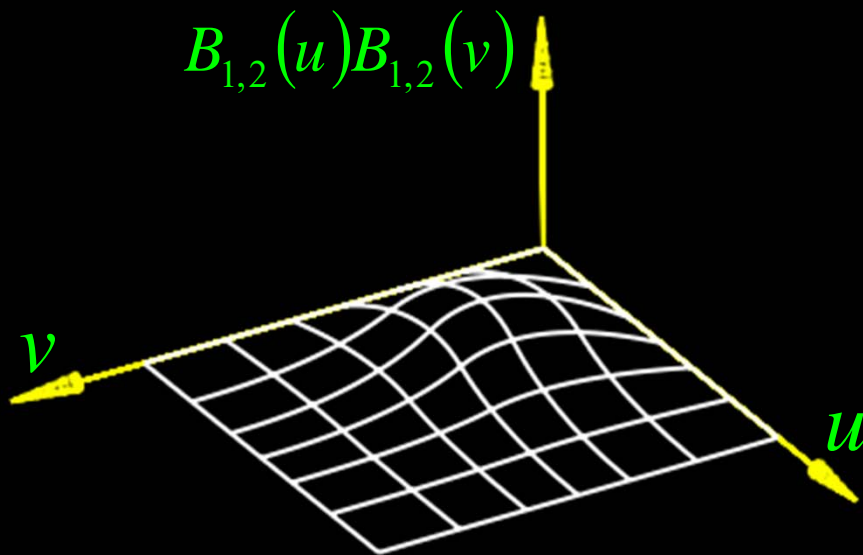
$$\tau_u = \tau_v = \{0, 0, 0, 1, 2, 2, 2\}.$$



B-spline Products (Cont.)

Example 13.5 (Cont.):

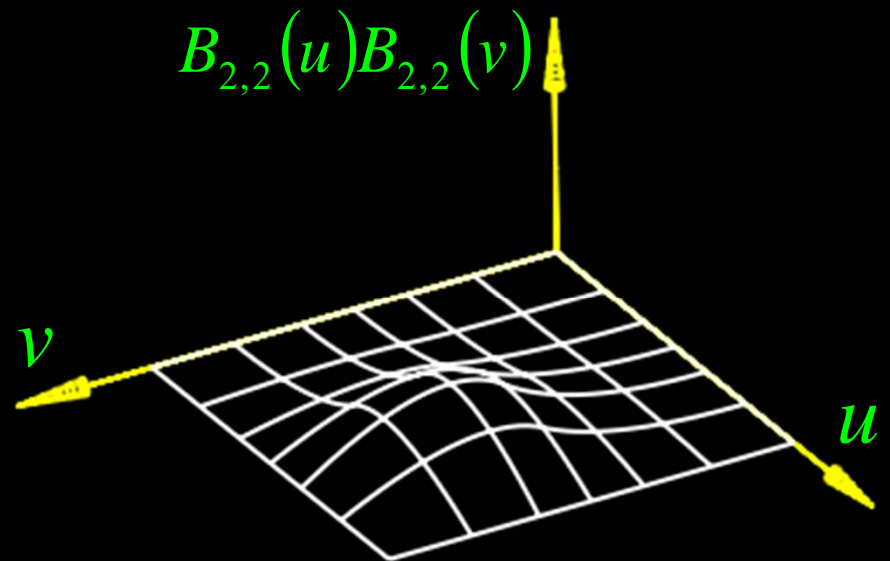
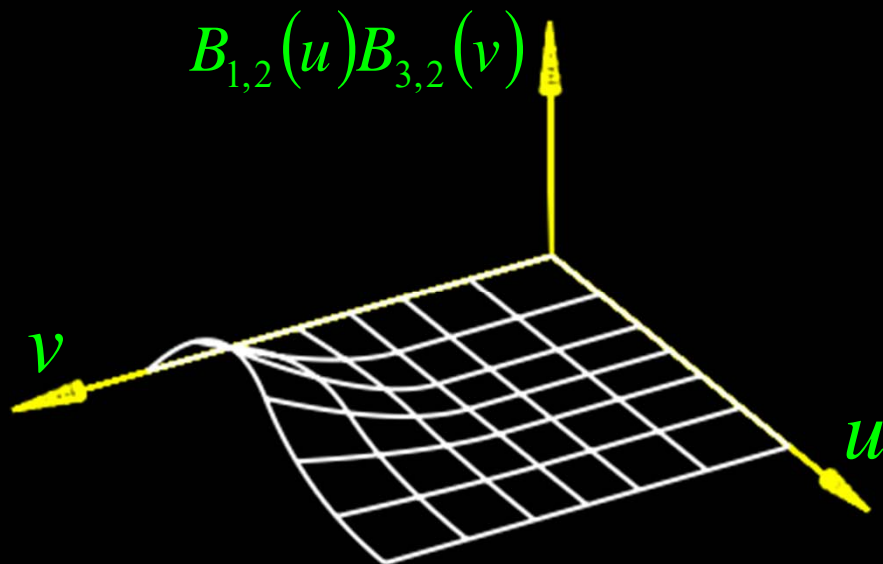
$$\tau_u = \tau_v = \{0, 0, 0, 1, 2, 2, 2\}.$$



B-spline Products (Cont.)

Example 13.5 (Cont.):

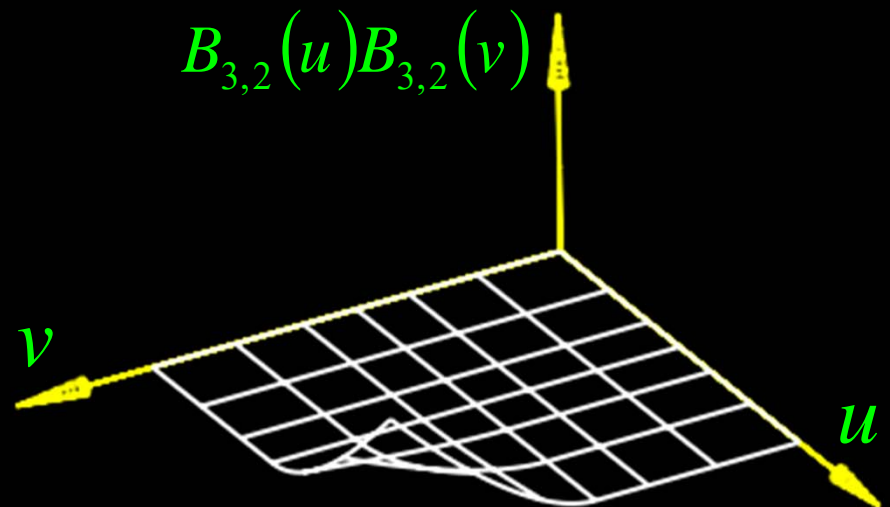
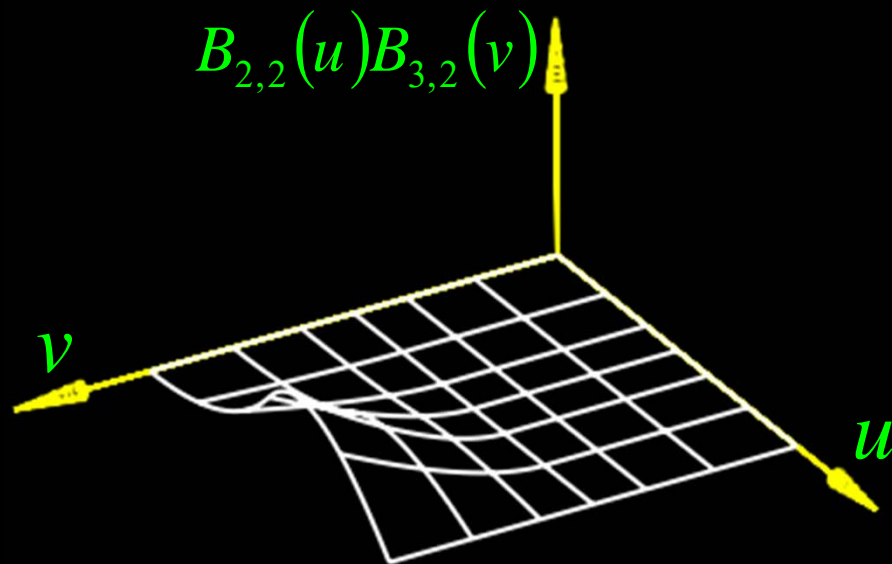
$$\tau_u = \tau_v = \{0, 0, 0, 1, 2, 2, 2\}.$$



B-spline Products (Cont.)

Example 13.5 (Cont.):

$$\tau_u = \tau_v = \{0, 0, 0, 1, 2, 2, 2\}.$$



Control Mesh

Definition 13.7:

The collection

$$P = \{ P_{i,j} \in R^3 \mid 0 \leq i \leq m, 0 \leq j \leq n \}$$

is called the **control mesh** for the Bezier/B-spline surface.

Convex Combination

Lemma 13.8:

Suppose $\sigma(u, v) = \sum_{j=0}^n \sum_{i=0}^m P_{i,j} B_{i,k_u, \tau_u}(u) B_{j,k_v, \tau_v}(v)$ is a tensor product B-spline surface, for the proper domain. Then

$$1 = \sum_{j=0}^n \sum_{i=0}^m B_{i,k_u, \tau_u}(u) B_{j,k_v, \tau_v}(v).$$

Convex Combination (Cont.)

Lemma 13.8 (cont.):

Proof: $\sum_{i=0}^m B_{i,k_u,\tau_u}(u) = 1, \quad \sum_{j=0}^n B_{j,k_v,\tau_v}(v) = 1.$

Then
$$\begin{aligned} \sum_{j=0}^n \sum_{i=0}^m B_{i,k_u,\tau_u}(u) B_{j,k_v,\tau_v}(v) &= \sum_{j=0}^n \left(\sum_{i=0}^m B_{i,k_u,\tau_u}(u) \right) B_{j,k_v,\tau_v}(v) \\ &= \sum_{j=0}^n B_{j,k_v,\tau_v}(v) \\ &= 1. \end{aligned}$$

Surface Evaluation

Consider $\sigma(u, v) = \sum_{i=0}^m \sum_{j=0}^n P_{i,j} B_{j,k_v,\tau_v}(v) B_{i,k_u,\tau_u}(u),$

and $\varphi(u, v) = \sum_{j=0}^n \sum_{i=0}^m P_{i,j} B_{i,k_u,\tau_u}(u) B_{j,k_v,\tau_v}(v).$

Question: What is the difference between $\sigma(u, v)$ and $\varphi(u, v)$?

Partial Derivatives' Evaluation

Consider $\sigma(u, v) = \sum_{j=0}^n \sum_{i=0}^m P_{i,j} B_{i,k_u, \tau_u}(u) B_{j,k_v, \tau_v}(v)$.

How can we compute $\frac{\partial \sigma(u, v)}{\partial u}$ and $\frac{\partial \sigma(u, v)}{\partial v}$?

$$\frac{\partial}{\partial u} \left(\sum_{j=0}^n \sum_{i=0}^m P_{i,j} B_{i,k_u, \tau_u}(u) B_{j,k_v, \tau_v}(v) \right) = \sum_{j=0}^n \frac{\partial}{\partial u} \left(\sum_{i=0}^m P_{i,j} B_{i,k_u, \tau_u}(u) \right) B_{j,k_v, \tau_v}(v).$$

Question: What about $\partial \sigma / \partial v$?

Tensor Product Example 1

Consider curve $C_1(u)$ and $C_2(v)$. Recall that if we seek the minimal distance between $C_1(u)$ and $C_2(v)$, we need to compute the extrema of:

$$\begin{aligned}\sigma(u, v) &= \|C_1(u) - C_2(v)\|^2 \\ &= \langle C_1(u) - C_2(v), C_1(u) - C_2(v) \rangle.\end{aligned}$$

To compute the extrema of $\sigma(u, v)$, we differentiate:

$$\frac{d\sigma(u, v)}{du} = 2\langle C_1'(u), C_1(u) - C_2(v) \rangle,$$

only to seek the simultaneous zeros of both partials.

$$\frac{d\sigma(u, v)}{du} = 2\langle C_1'(u), C_1(u) - C_2(v) \rangle$$

Tensor Product Example 1 (cont)

Question: How do we represent $C_1'(u)$ and $C_1(u) - C_2(v)$ as tensor product surface (bivariate), like $\sigma(u, v)$?

For $C_1'(u)$:

$$\begin{aligned} C_1'(u) &= \sum P_i \theta_i(u) \\ &= \sum P_i \theta_i(u) \sum \theta_j(v) \\ &= \sum \sum P_i \theta_i(u) \theta_j(v). \end{aligned}$$

$$\frac{d\sigma(u, v)}{du} = 2\langle C_1'(u), C_1(u) - C_2(v) \rangle$$

Tensor Product Example 1 (cont)

Same for $C_1(u) - C_2(v)$:

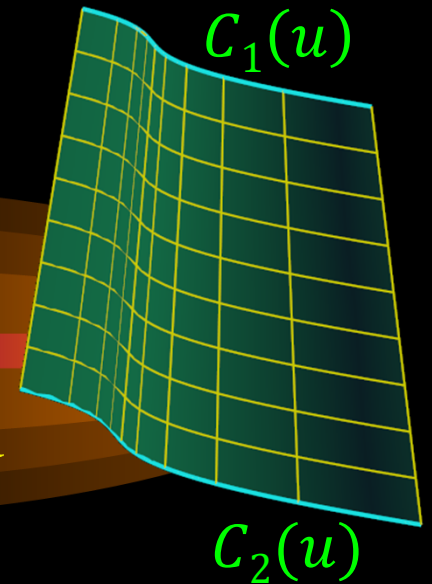
$$C_1(u) - C_2(v) =$$

$$= \sum P_i \theta_i(u) - \sum Q_j \theta_j(v)$$

$$= \sum P_i \theta_i(u) \sum \theta_j(v) - \sum Q_j \theta_j(v) \sum \theta_i(u)$$

$$= \sum \sum (P_i - Q_j) \theta_i(u) \theta_j(v).$$

Tensor Product Example 2



Consider two curves $C_1(u) = \sum P_i \theta_i(u)$ and $C_2(u) = \sum Q_i \theta_i(u)$, $u \in [0,1]$, and compute the ruled surface between them:

$$\begin{aligned}\sigma(u, v) &= C_1(u)(1 - v) + C_2(u)v, \quad v \in [0,1] \\ &= \sum P_i \theta_i(u) (1 - v) + \sum Q_i \theta_i(u) v \\ &= \sum P_i \theta_i(u) \theta_{0,1}(v) + \sum Q_i \theta_i(u) \theta_{1,1}(v) \\ &= \sum_{j=0}^1 \sum R_{ij} \theta_i(u) \theta_{j,1}(v),\end{aligned}$$

where $R_{ij} = P_i$ for $j = 0$ and $R_{ij} = Q_i$ for $j = 1$.

Tensor Product Example 3

Consider two tensor product surfaces

$$S_1(u, v) = \sum \sum P_{ij} \theta_i(u) \theta_j(v) \text{ and}$$

$$S_2(u, v) = \sum \sum Q_{ij} \theta_i(u) \theta_j(v),$$

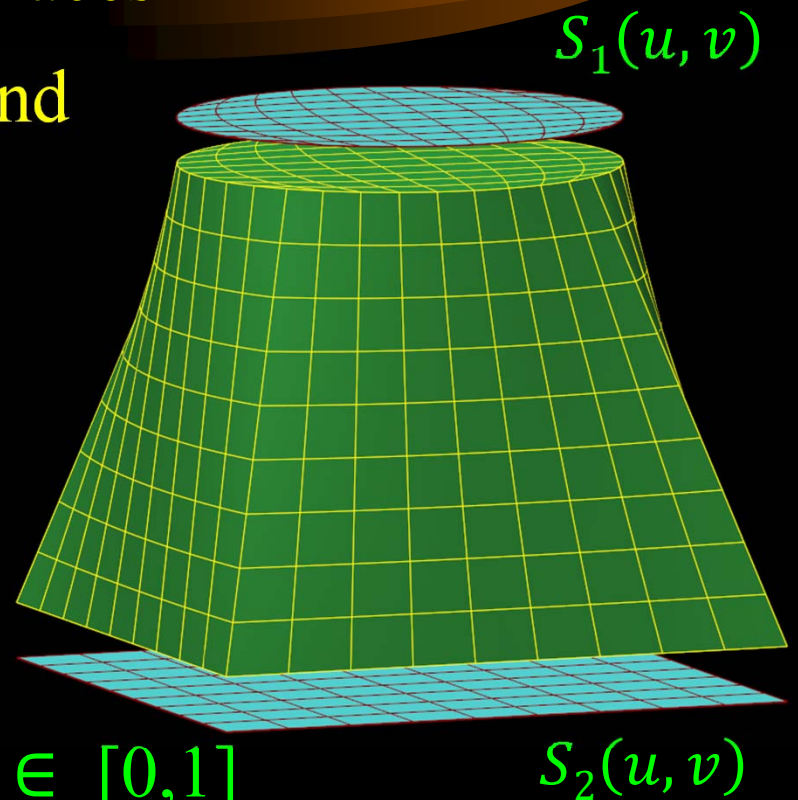
$$u, v \in [0, 1],$$

and compute the

ruled trivariate between them:

$$T(u, v, w) =$$

$$S_1(u)(1 - w) + S_2(u)w, \quad w \in [0, 1]$$



Tensor Product Example 3 (cont.)

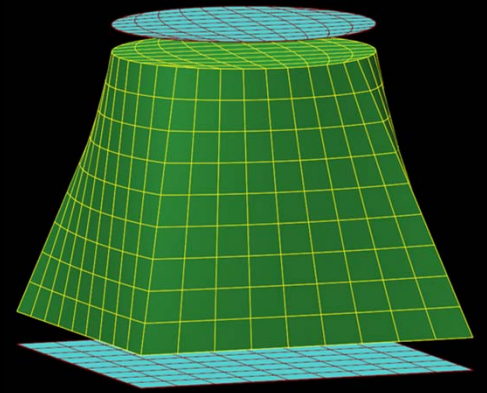
$$T(u, v, w) = S_1(u)(1 - w) + S_2(u)w, \quad w \in [0,1]$$

$$= \sum \sum P_{ij} \theta_i(u) \theta_j(v) (1 - w) + \sum \sum Q_{ij} \theta_i(u) \theta_j(v) w$$

$$= \sum \sum P_{ij} \theta_i(u) \theta_j(v) \theta_{0,1}(w) + \sum \sum Q_{ij} \theta_i(u) \theta_j(v) \theta_{1,1}(w)$$

$$= \sum_{k=0}^1 \sum \sum R_{ijk} \theta_i(u) \theta_j(v) \theta_{k,1}(w),$$

where $R_{ijk} = P_{ij}$ for $k = 0$ and $R_{ijk} = Q_{ij}$ for $k = 1$.



Tensor Product Example 3 (cont.)

$T(u, v, w)$ represents a solid object. Meaning T represents both the boundary of the geometry and its interior, which, for example, can be heterogeneous.

Very important, for example, for:

- ❑ 3D printing of heterogeneous materials:
- ❑ Analysis (stress/heat transfer, etc.).



Tensor Product Example 4

- ❑ We talked about curves, surfaces, and trivariates.
- ❑ Generalizing, we can talk about **multivariate** functions in the Bezier and B-spline.
- ❑ This allows us to represent arbitrary polynomials function in any dimension and range.
- ❑ Opens up whole new areas of research,
 - ❑ Work in multivariate constraints solving.

