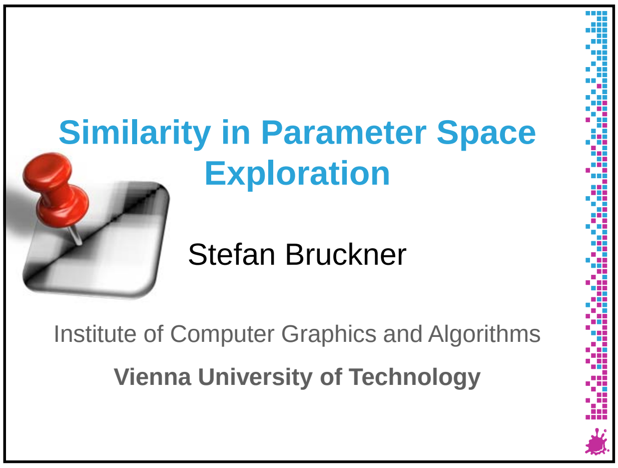

# Similarity in Parameter Space Exploration

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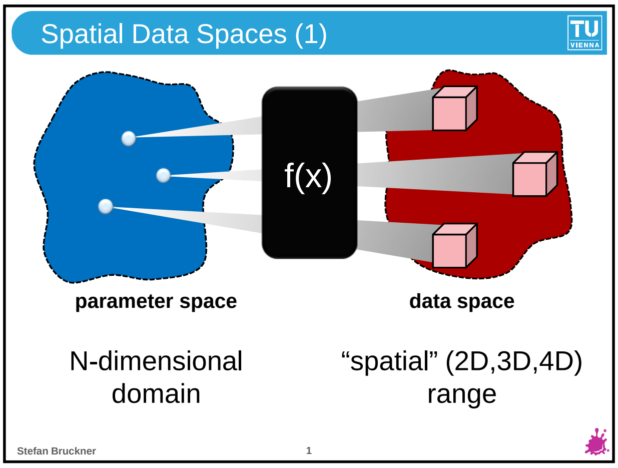
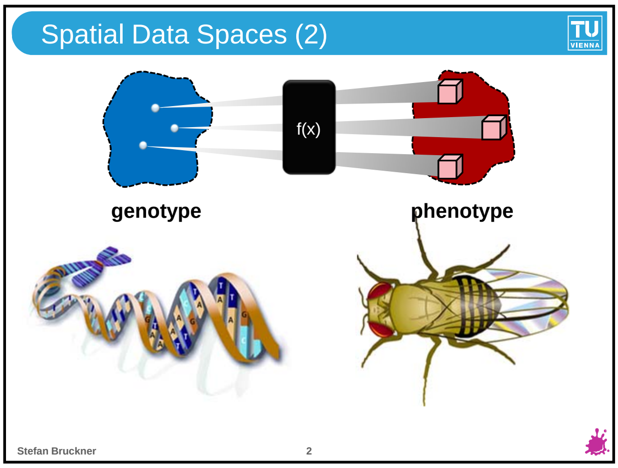


## Spatial Data Spaces (1)

**parameter space** — N-dimensional domain

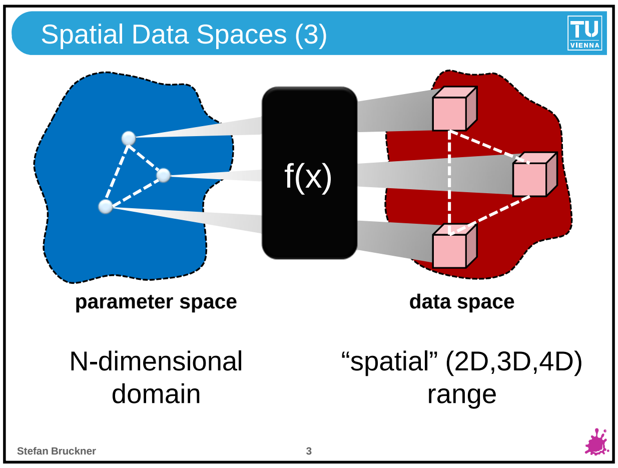
**data space** — “spatial” (2D,3D,4D) range



## Spatial Data Spaces (2)

**genotype**

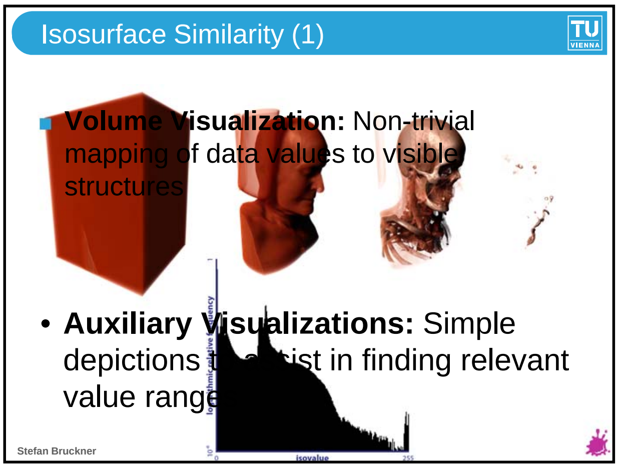
**phenotype**



## Spatial Data Spaces (3)

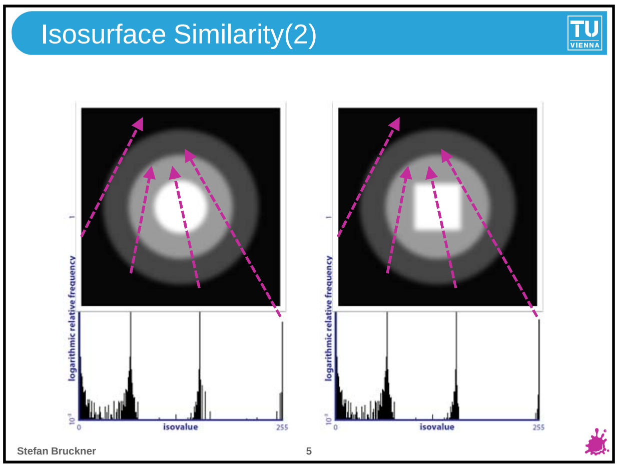
**parameter space** — N-dimensional domain

**data space** — “spatial” (2D,3D,4D) range



## Isosurface Similarity (1)

- **Volume Visualization:** Non-trivial mapping of data values to visible structures
- **Auxiliary Visualizations:** Simple depictions that assist in finding relevant value ranges



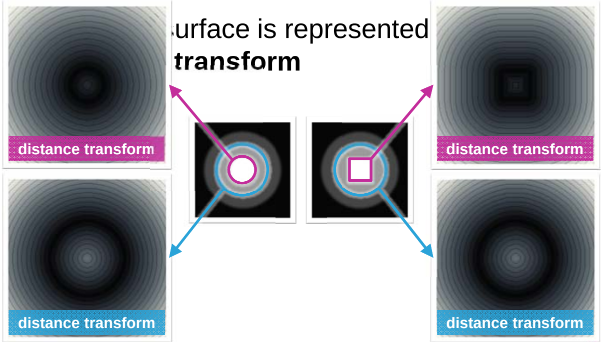
## Isosurface Similarity(2)

## Similarity Maps – Key Aspects

- **Treat isosurfaces as a whole** instead of individual voxels
- **Characterize the shape** of every isosurface
- **Quantify their similarity** by comparing all isosurface shapes

## Isosurface Representation

urface is represented
**transform**



## Similarity Measure (1)

- Regard the distances to a pair of isosurfaces as **random variables** $X$, $Y$
  - Characterize the amount of information they share to evaluate similarity
- **Mutual Information:** Commonly used information-theoretic measure
  - Measures how much knowing one variable reduces the uncertainty about the other

## Similarity Measure (2)

**Mutual Information**

$$I(X,Y) = \overbrace{H(X)+H(Y)}^{\text{marginal entropies of } X,\, Y} - \underbrace{H(X,Y)}_{\text{joint entropy of } X \text{ and } Y}$$

- $X$ and $Y$ are **independent**: $I(X,Y) = 0$
- $X$ and $Y$ are **identical**: $I(X,Y) = H(X) = H(Y)$

normalized measure
$$\hat{I}(X,Y) = \frac{2I(X,Y)}{H(X)+H(Y)}$$

## Similarity Measure (3)

**Joint Entropy**

$$H(X,Y) = -\sum_{x\in X}\sum_{y\in Y}\underbrace{p_{X,Y}(x,y)}\log\left(\underbrace{p_{X,Y}(x,y)}\right)$$

joint probability distribution of $X$ and $Y$

- Requires knowledge of the **joint probability distribution** of $X$ and $Y$
- Simple estimation method using the **joint histogram** of $X$ and $Y$

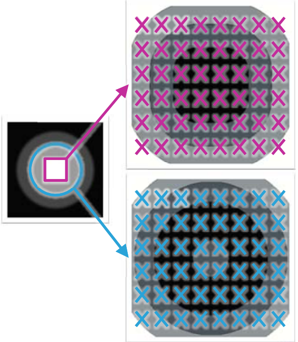
## Joint Distribution Estimation

joint distribution $p_{X,Y}$

isosurface $h_1$

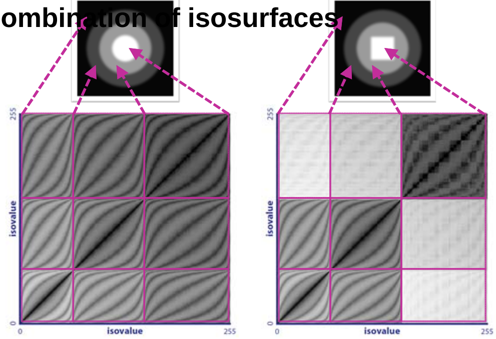
isosurface $h_2$

| | $d_1$ | $d_2$ | $d_3$ | $d_4$ |
|---|---|---|---|---|
| $d_1$ | 0.25 | 0.333 | 0 | 0 |
| $d_2$ | 0 | 0.083 | 0.25 | 0 |
| $d_3$ | 0 | 0 | 0.083 | 0 |
| $d_4$ | 0 | 0 | 0 | 0 |

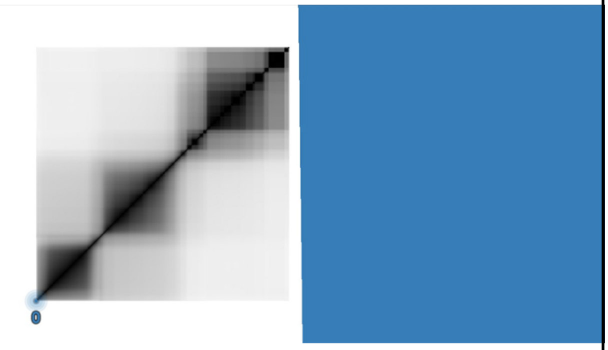


## Isosurface Similarity Map

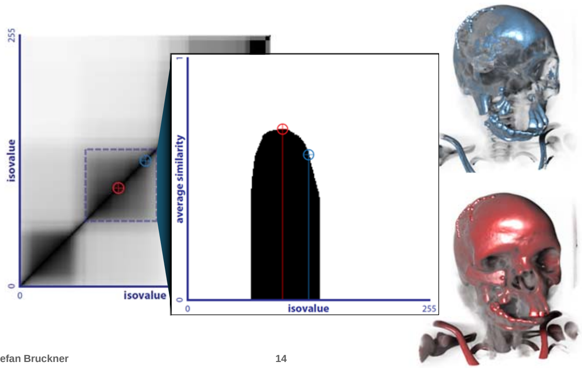
- Depicts the **mutual information** of **each combination of isosurfaces**



## Similarity-Enhanced Isosurfaces (1)



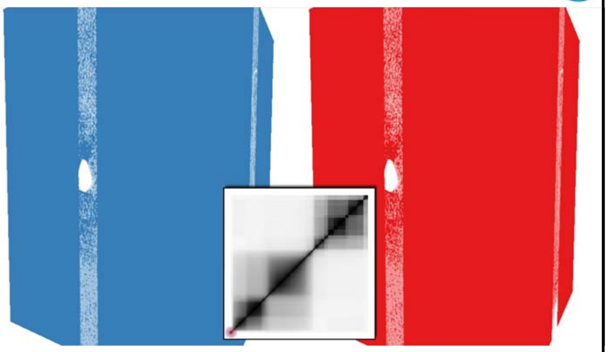
## Similarity-Enhanced Isosurfaces (2)



## Similarity-based Remapping (1)

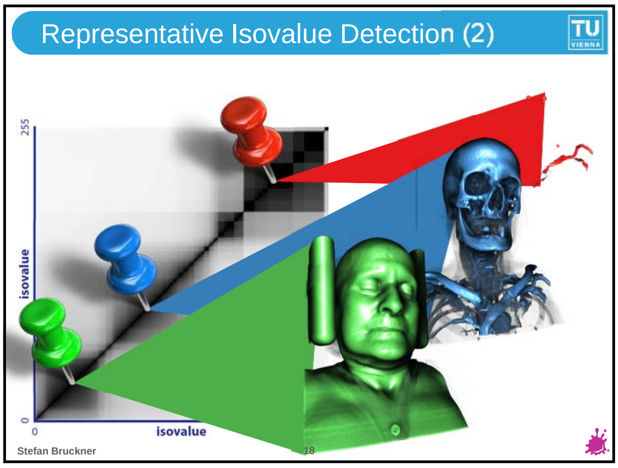
- Mapping between user interface and isovalue is typically linear
  - Examples are slider widgets, mouse movement, etc.
  - Data-dependent nonlinear visual response to user interaction
  - Makes it more difficult to investigate transitional value ranges
- Control derivative of the mapping function using the similarity between neighboring isovalues

## Similarity-based Remapping (2)

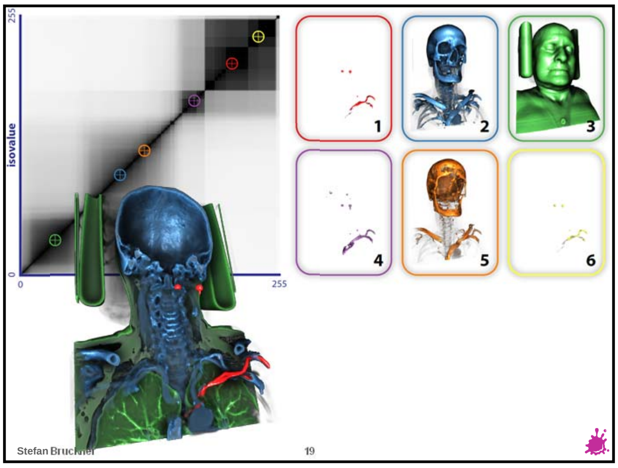


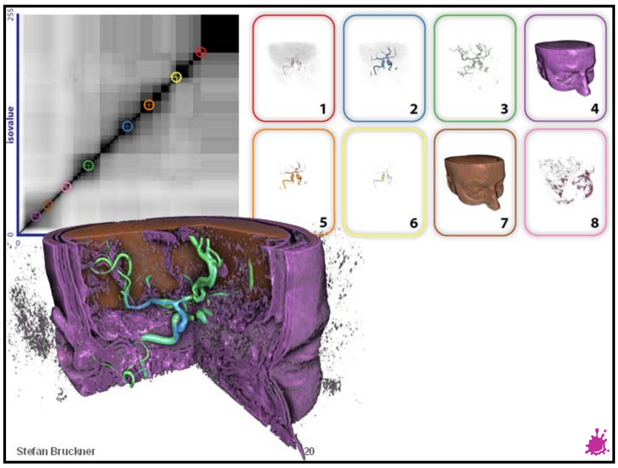
## Representative Isovalue Detection (1)

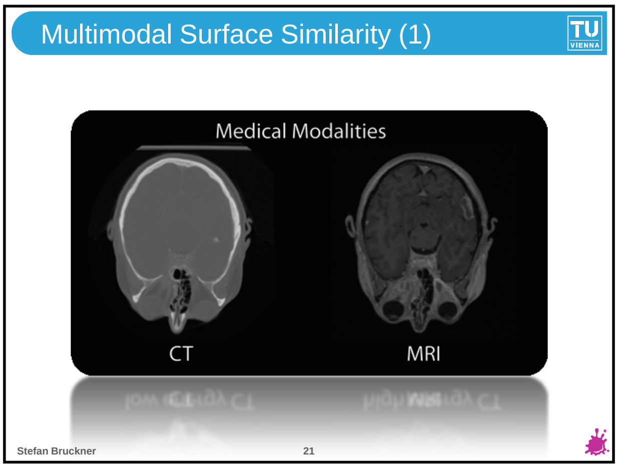
- Find “good” isovalues for a given data set without requiring parameter tuning
  - **Representative:** Each isovalues exhibits high similarity to many other isovalues
  - **Distinct:** The individual chosen isovalues have low mutual similarity
- Reorder all isovalues according to these criteria by recursively evaluating the similarity distribution



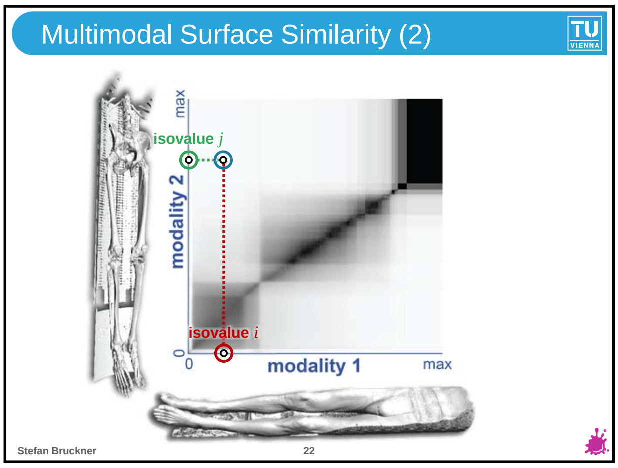
## Representative Isovalue Detection (2)



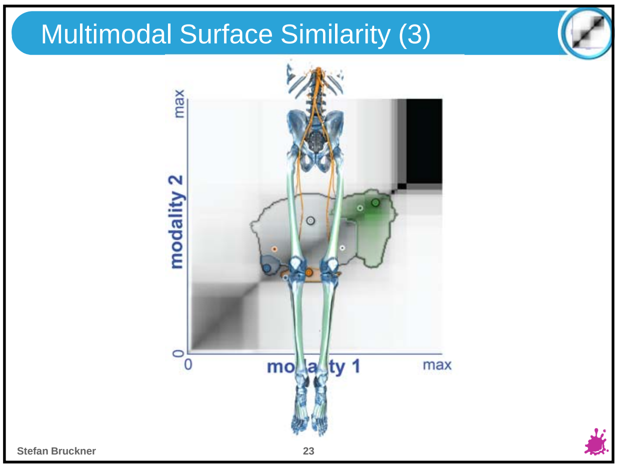




## Multimodal Surface Similarity (1)

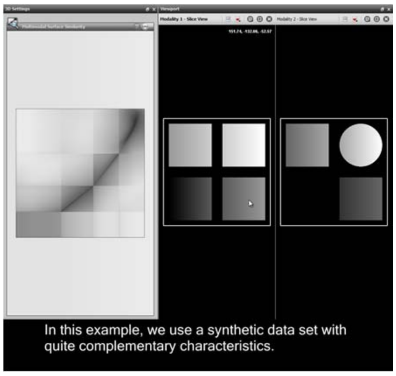


## Multimodal Surface Similarity (2)



## Multimodal Surface Similarity (3)

## Similarity-Based Classification



In this example, we use a synthetic data set with quite complementary characteristics.

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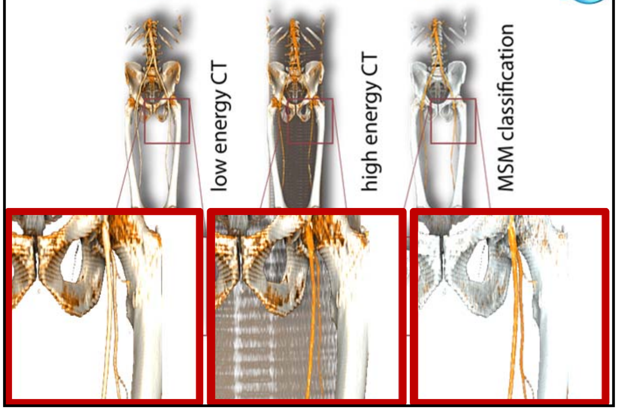
## Similarity-Based Classification (2)



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## Similarity-Based Classification (3)

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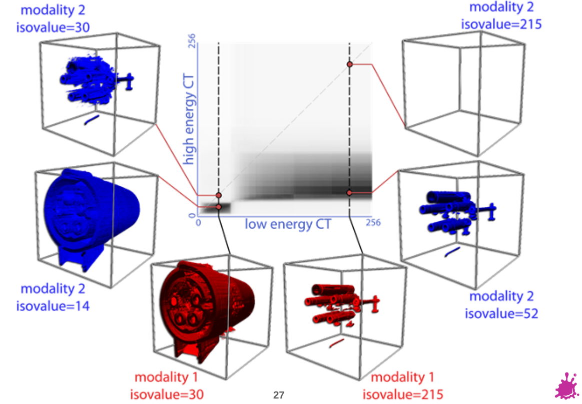
## Maximum Similarity Isosurfaces (1)



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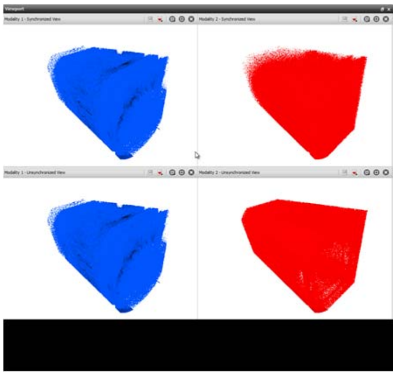
## Maximum Similarity Isosurfaces (2)



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## Conclusions

- Spatial similarity measures can help us to guide visual exploration
- Provide insight into the stability of regions in parameter space
- Task-dependent: difficult to find “one measure to rule them all”
- Future: Dynamic measures, incorporate user knowledge