Interactive Visual Analysis of Medical Data

Tutorial: Interactive Visual Analysis of Scientific Data

Steffen Oeltze

Outline

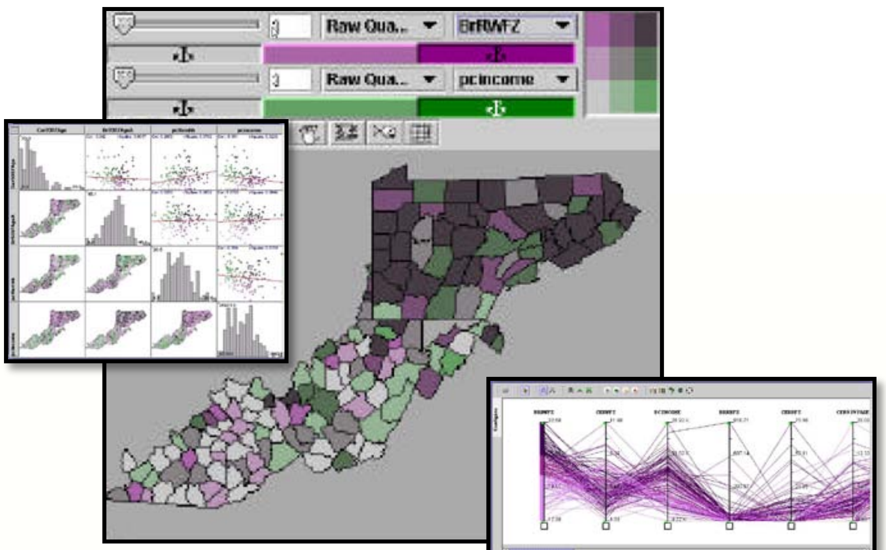
- Motivation
- Application Examples
- IVA of Perfusion Data
- Summary

Motivation

- Enormous variety of data can be acquired for a single patient, a group of patients, or a cohort of (healthy) subjects
- Image data
  - CT,MRI,US,PET,SPECT,…
  - Spatiotemporal, multi-field and multi-modal data
- Non-image data
  - Laboratory tests, ECG, patient history, data derived from image data…
  - Very heterogeneous, i.e. different data types, dimensions
- IVA can:
  - Guide the user to interesting portions of the complex data
  - Confirm or generate hypotheses based on the data
- Data organization prior to IVA is a challenge!

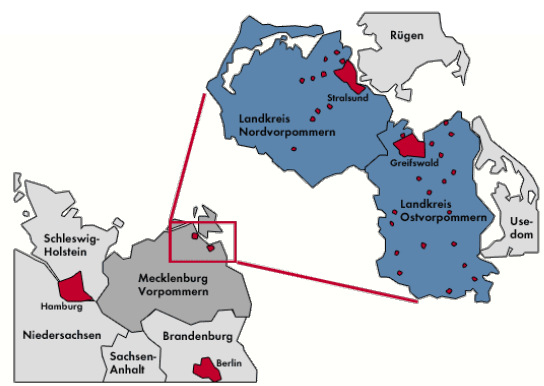
Applications – Epidemiology

- Accomplishment of cohort studies
  - Hundreds or thousands of subjects
  - Analysis of life history, risk factors and correlations
  - Complex, heterogeneous and often longitudinal data
  - Often, related to geographic information



Dai and Gahegan, 2005

Study of Health in Pomerania (SHIP):
•Three waves with 2500-4308 subjects
•Includes extensive MRI protocol

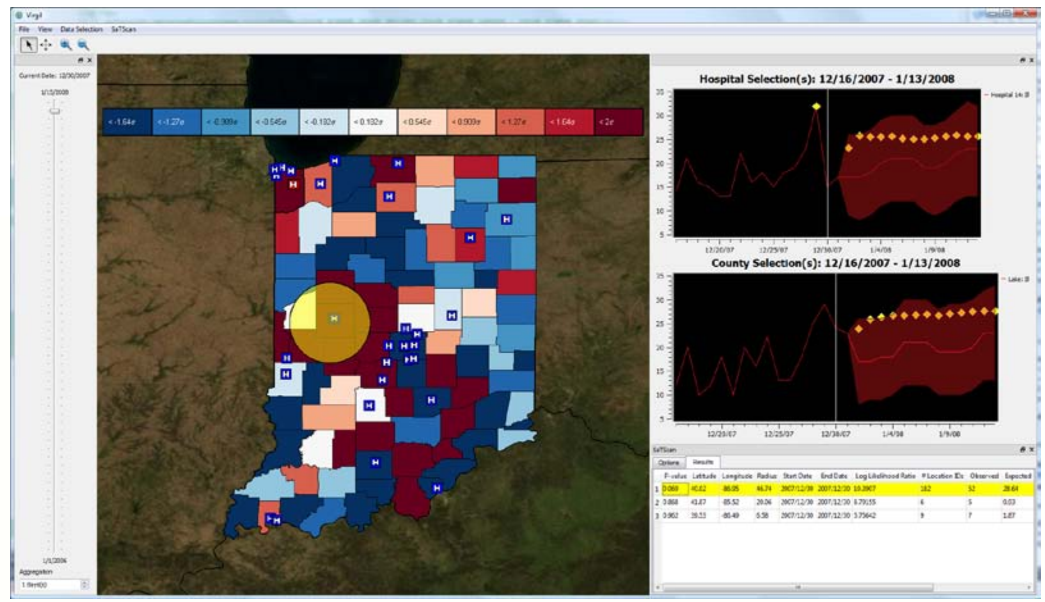


Völzke et al., 2011

Applications – Public Health

- IVA of electronic health records:
  - Diagnosing a single patient based on his/her history
  - Measuring healthcare quality by analyzing multiple patients
- IVA of data from syndromic surveillance:
  - Detect or anticipate disease outbreaks

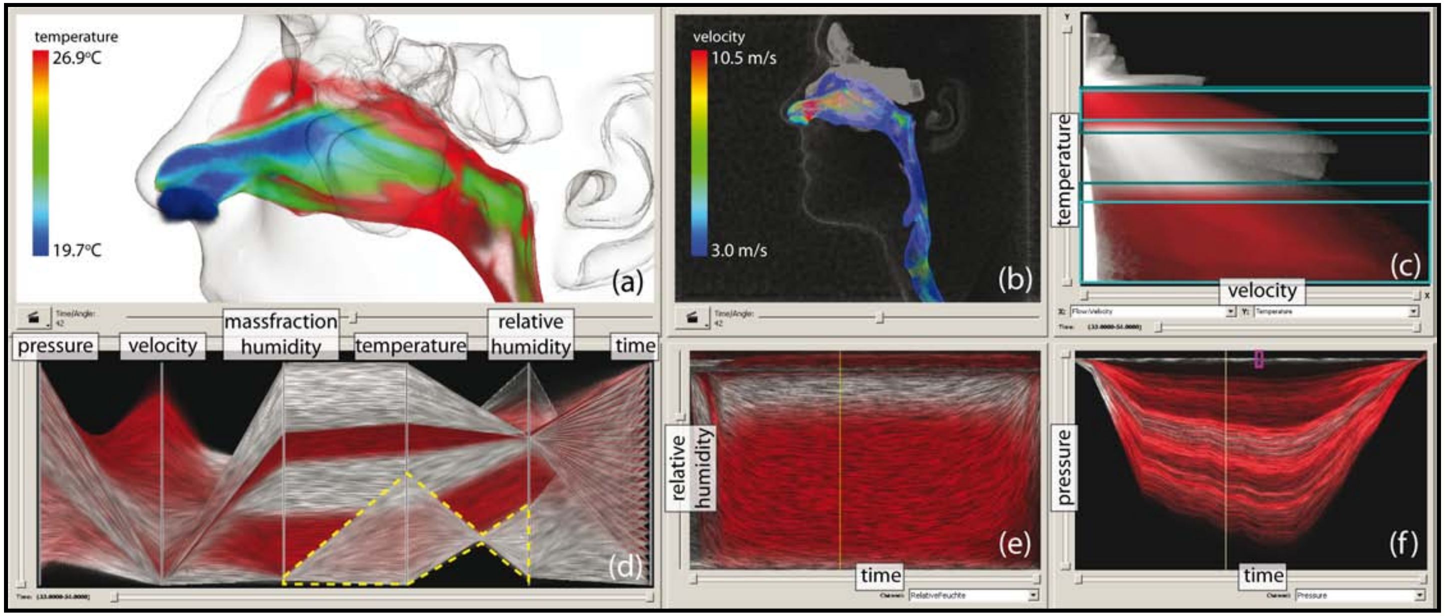
Wang, 2011



Maciejewski, 2011

Applications – Simulation Data

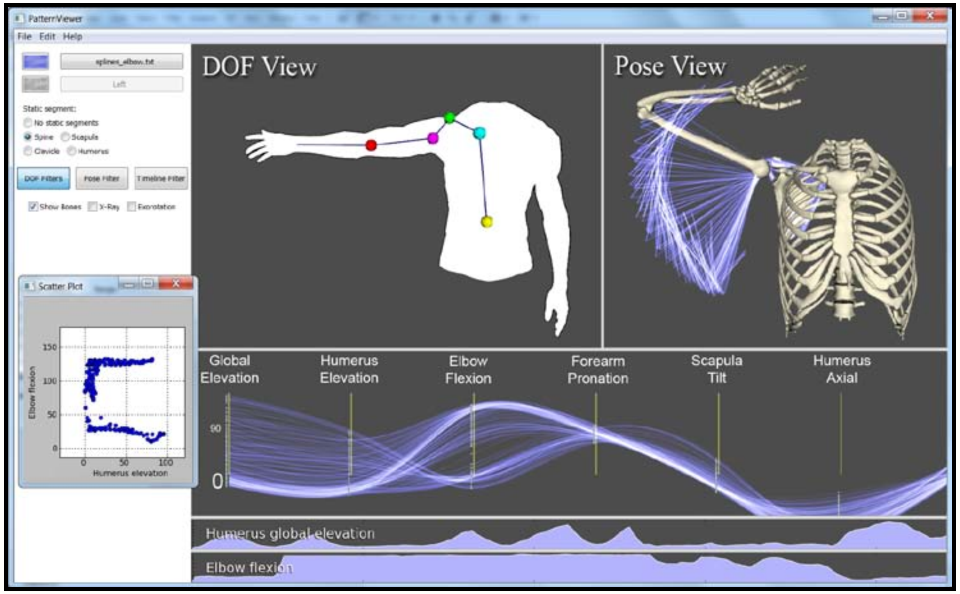
- CFD simulations, e.g., of blood flow and nasal airflow, simulation of joint kinematics and cardiac electrophysiology
  - Large, complex and often time-dependent data
  - Multiple computed and derived attributes
  - Investigation of modeling and simulation parameters



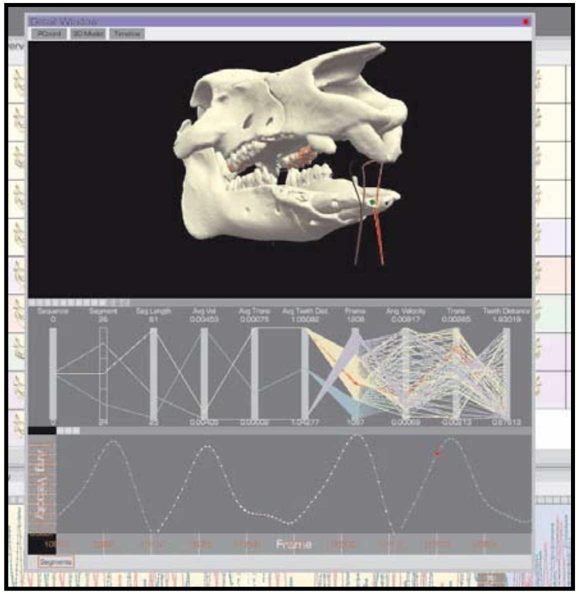
Zachow et al., 2009

Applications – Kinematics Data

- Acquired by motion tracking, imaging systems or simulations
  - Time-dependent data, geometry changes over time
  - Multiple computed and derived attributes
  - Understanding joint behavior, e.g., for assessing fracture healing or for planning and evaluating orthopedic surgery



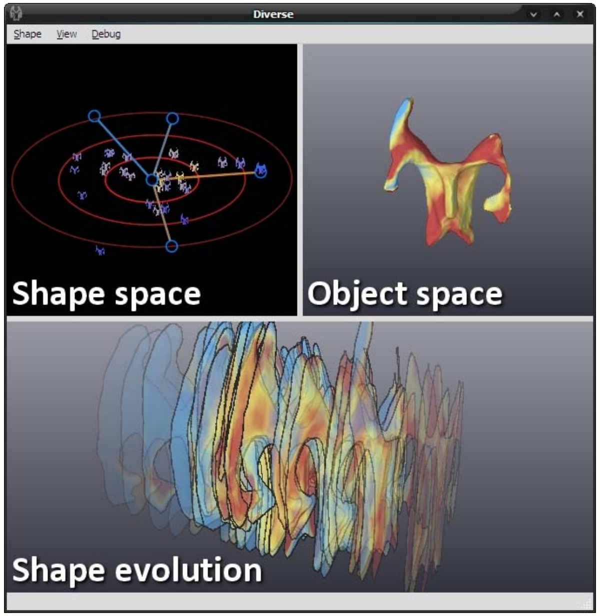
Krekel et al., 2010

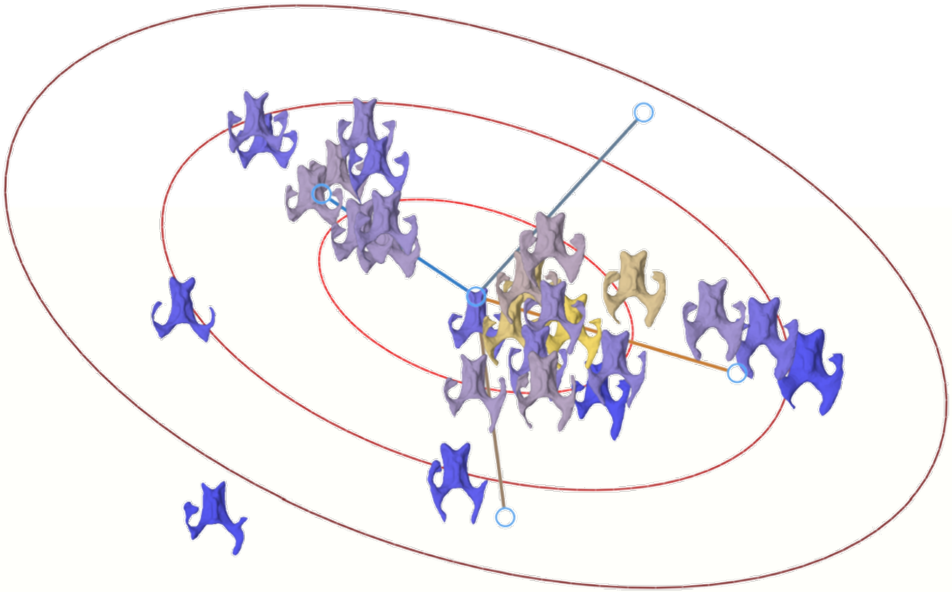


Keefe et al., 2009

Applications – Statistical Data

- Visualizing Anatomic Shape Variability in a Population
  - Variability described by statistical shape model
  - IVA to explore and navigate shape space
  - Detection of changes in organ anatomy and correlation with risk factors, e.g., liver shape, alcohol and adiposity

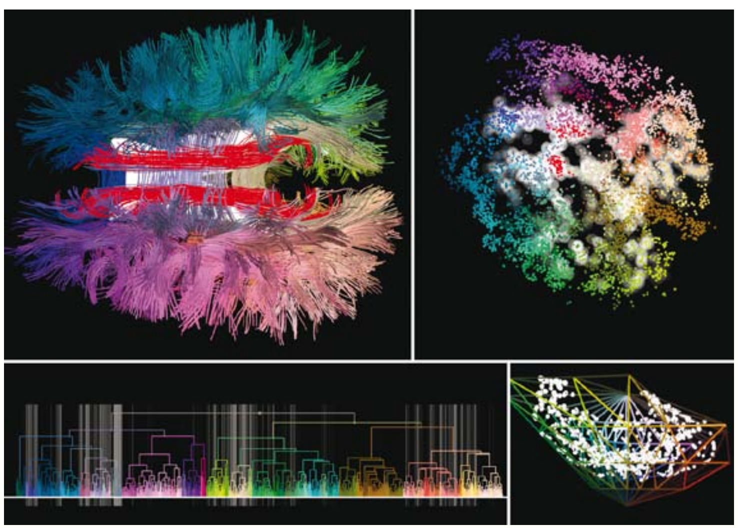




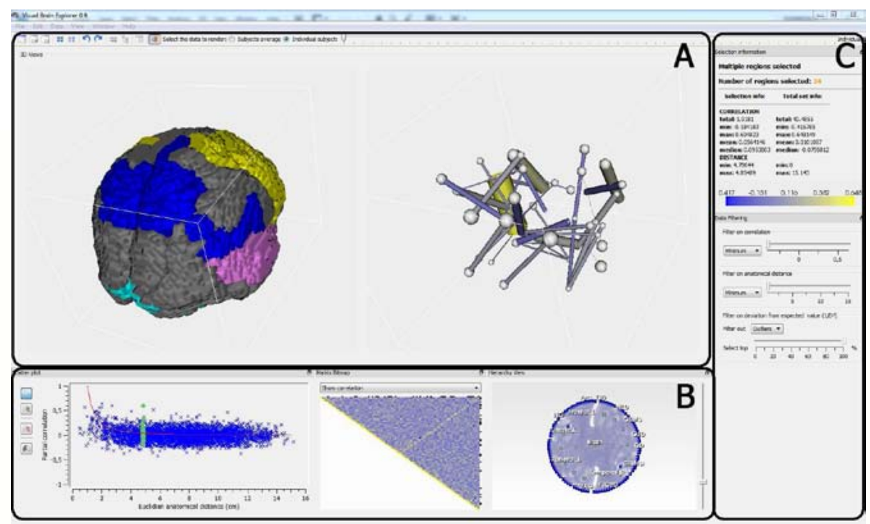
Busking et al., 2010

Applications – DTI and rs-fMRI Data

- Diffusion Tensor Imaging (DTI) data
  - Water diffusion indicates direction of major fiber tracts
  - IVA helps in exploring the very complex fiber tracts
- resting state-functional MRI (rs-fMRI) data
  - Measuring BOLD contrast to evaluate brain activity
  - IVA of functional brain connectivity



Jianu et al., 2009



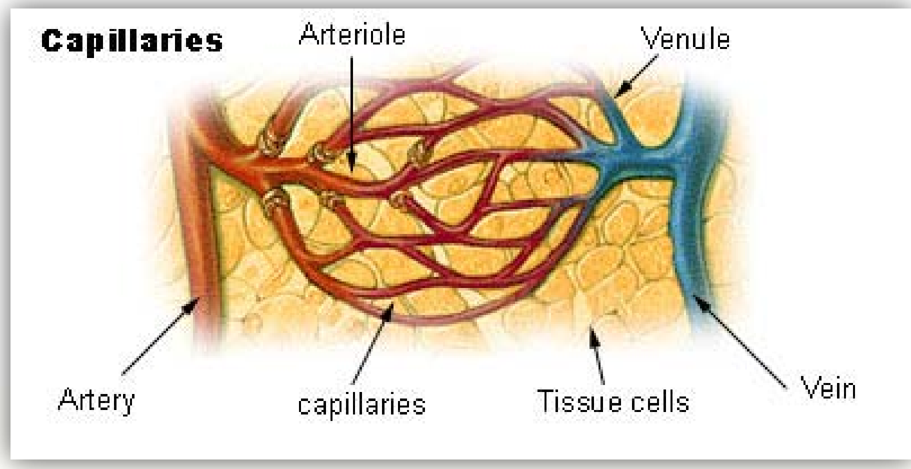
Dixhoorn et al., 2010

Interactive Visual Analysis of Perfusion Data

B. Preim, S. Oeltze, M. Mlejnek, E. Gröller, A. Hennemuth, S. Behrens: *Survey of the Visual Exploration and Analysis of Perfusion Data*. IEEE Trans. Vis. Comput. Graph. 15(2): 205-220 (2009)

Medical Background

- Measuring microcirculation of blood through tissue capillaries
- Capillaries below resolution of today's scanning devices
- Derivation of macroscopic parameters from measured data
- Example parameters:
  - Regional blood flow,
  - Regional blood volume,
  - Capillary permeability



http://en.wikipedia.org/wiki/Capillary

- Major application areas:
  - Ischemic stroke diagnosis,
  - Diagnosis of Coronary Heart Disease (CHD),
  - Breast tumor diagnosis

Perfusion Imaging

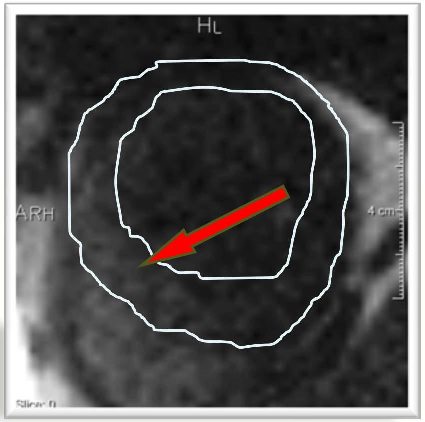
- Focus on perfusion Magnetic Resonance Imaging (MRI)
- Rapid injection of contrast agent (CA) to form a *bolus*
- CA accumulation causes signal changes ➔ perfusion tracer
- Application of fast sequences for imaging the CA's first pass
- Repeated acquisition of an image stack

Image Data and Data Preprocessing

- Typical dataset characteristics:
  - Ischemic stroke diagnosis
    - T2-weighted imaging
    - 128^2 x 10-15, every 1-2s over 40-80s
  - CHD diagnosis
    - T1-weighted imaging
    - 128^2-256^2 x 3-6, every heart beat over 30-60s
  - Breast tumor diagnosis
    - T1-weighted imaging
    - 512^2 x 80-100, every 2-5min over 10min

Cerebral perfusion

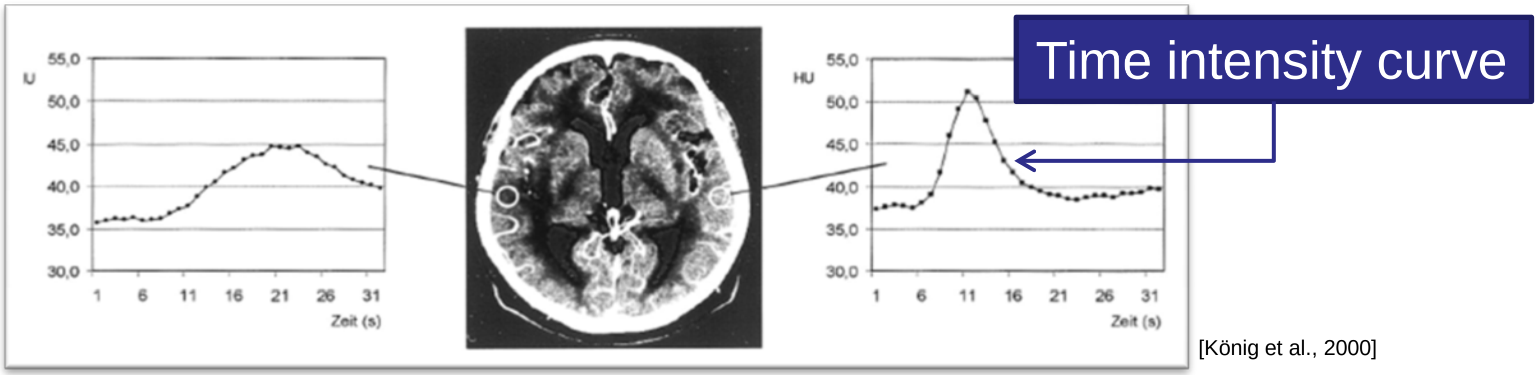
Myocardial perfusion



- Crucial data preprocessing steps:
  - Motion correction, signal intensity calibration, denoising

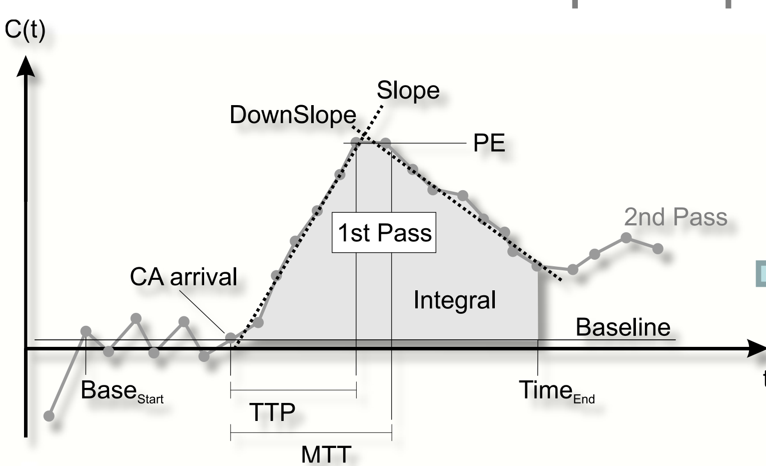
Diagnostic Evaluation of Perfusion Data

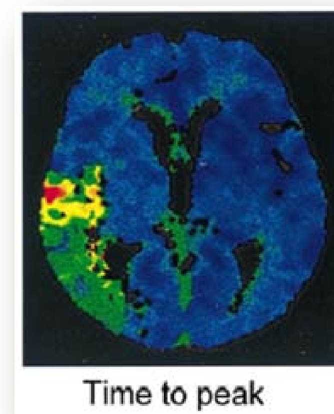
- “Eye balling” by means of *cine-movies*
- Time intensity curve-probing based on user-defined ROIs



[König et al., 2000]

- Evaluation based on descriptive perfusion parameters





[König et al., 2000]

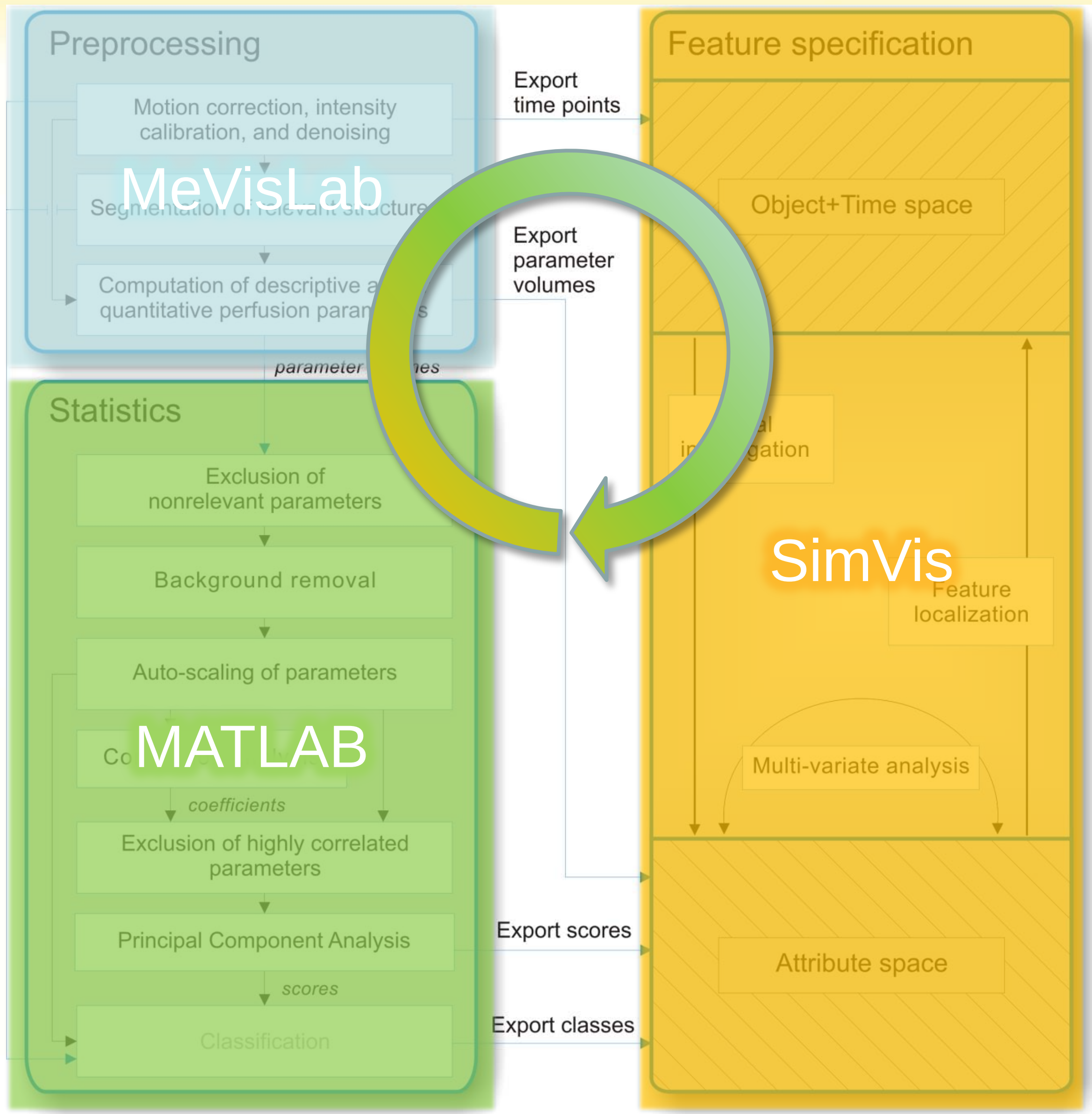
Motivation for IVA

- Complex time-dependent and multivariate data
- Non-standardized signal intensity and parameter domains
- Diagnostic evaluation requires filtering and feature detection
- Research on perfusion MRI, particularly in ischemic stroke, brain tumor, and CHD diagnosis:
  - Which perfusion parameter(s) derived by which computational method(s) best identify ischemic tissue?
  - How do varying imaging parameters and parameterizations of preprocessing methods effect reliability of perfusion parameters and computational methods?

➔IVA approach integrating techniques for data pre-processing, statistical analysis as well as feature specification

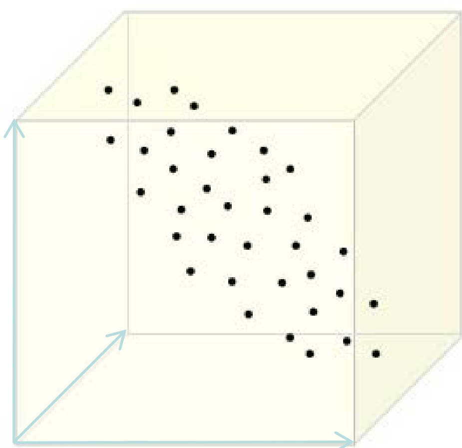
Visual Analysis Approach

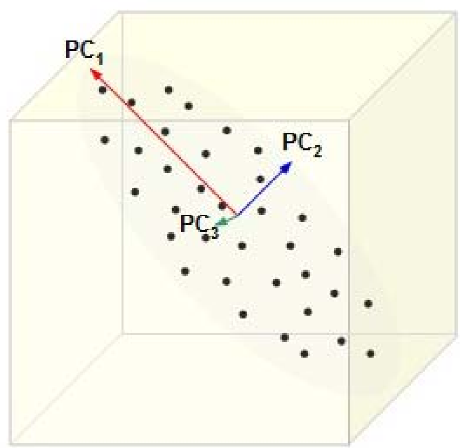
- Approach consists of components for data preprocessing, statistical analysis, and interactive feature specification
- Each component is implemented in a different software program



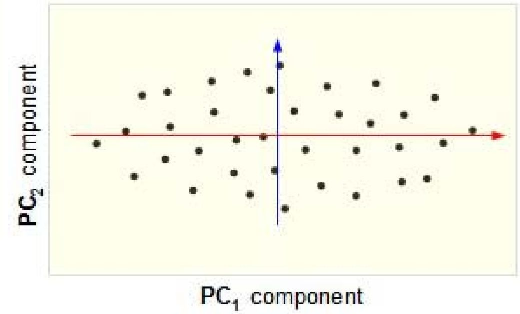
Principal Component Analysis

- Explains structure in the relationships between variables
- Reveals redundant variables and *trends* in the data
- Variance maximum rotation of data space ➔ new *pc-space*
- PCA results:
  - Pcs sorted by their *significance level* (variance explained by pc)
  - *Loadings* representing the basis vectors of the pc-space
  - *Scores* representing the coordinates in the pc-space





http://cnx.org/content/m11461/latest/



Case Studies

S. Oeltze, H. Doleisch, H.Hauser, P. Muigg, B. Preim: *Interactive Visual Analysis of Perfusion Data*. IEEE Trans. Vis. Comput. Graph. 13(6): 1392-1399 (2007)

S. Oeltze, H. Hauser, J. Rorvik, A. Lundervold, B. Preim: *Visual Analysis of Cerebral Perfusion Data -- Four Interactive Approaches and a Comparison*. Proc. of ISPA (588-595), 2009

S. Glaßer, U. Preim, K.D. Tönnies, B. Preim: *A visual analytics approach to diagnosis of breast DCE-MRI data*. Computers & Graphics 34(5): 602-611 (2010)

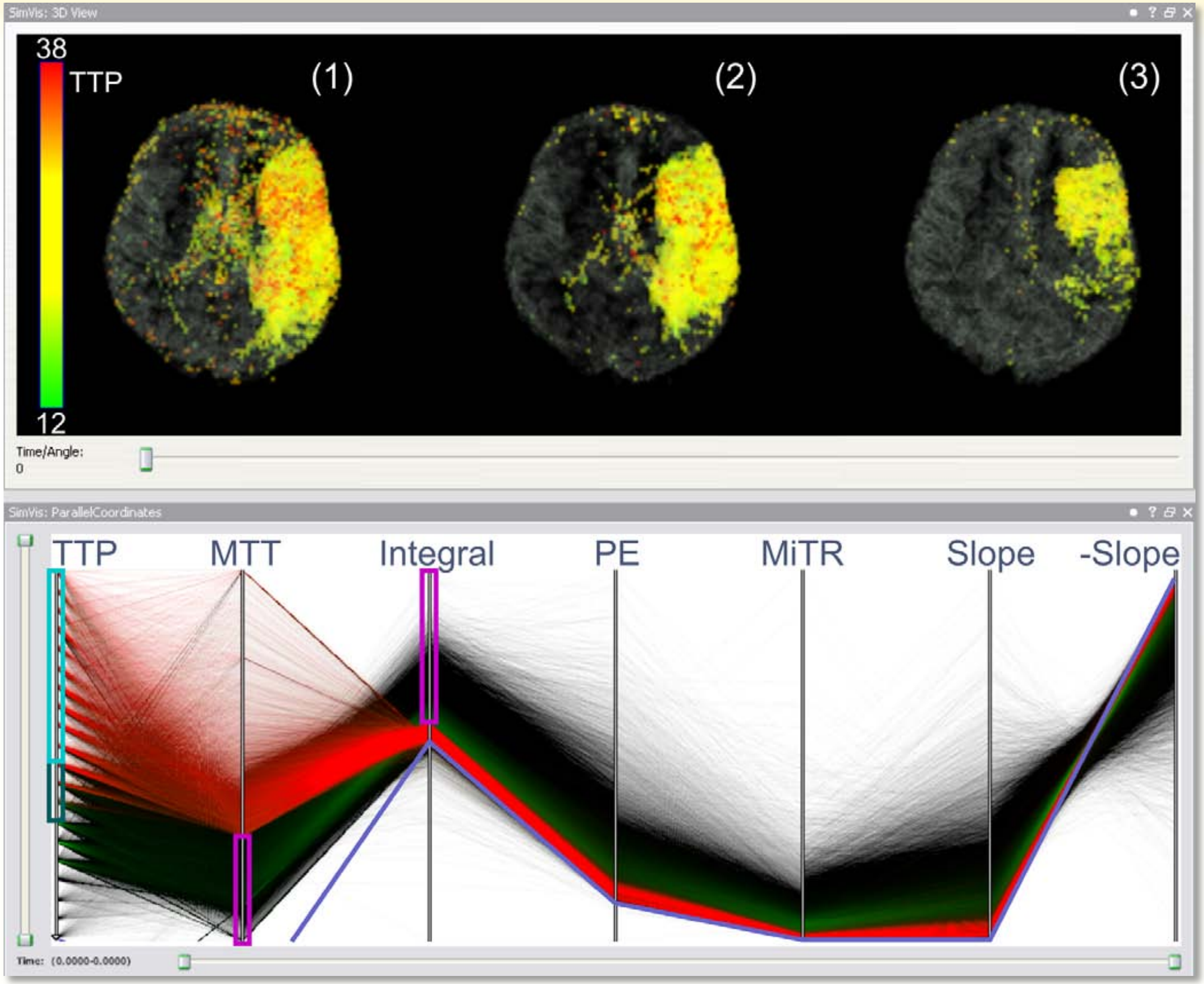
U. Preim, S. Glaßer, B. Preim, F. Fischbach, J. Ricke: Computer-aided diagnosis in breast DCE-MRI--quantification of the heterogeneity of breast lesions. Eur J Radiol 81(7):532-538 (2011)

S. Glaßer, S. Oeltze, U. Preim, A. Bjornerud, H. Hauser, B. Preim: *Visual analysis of longitudinal brain tumor perfusion*. Proc. of SPIE Medical Imaging, 2013

Ischemic Stroke Diagnosis

Analysis based on descriptive perfusion parameters

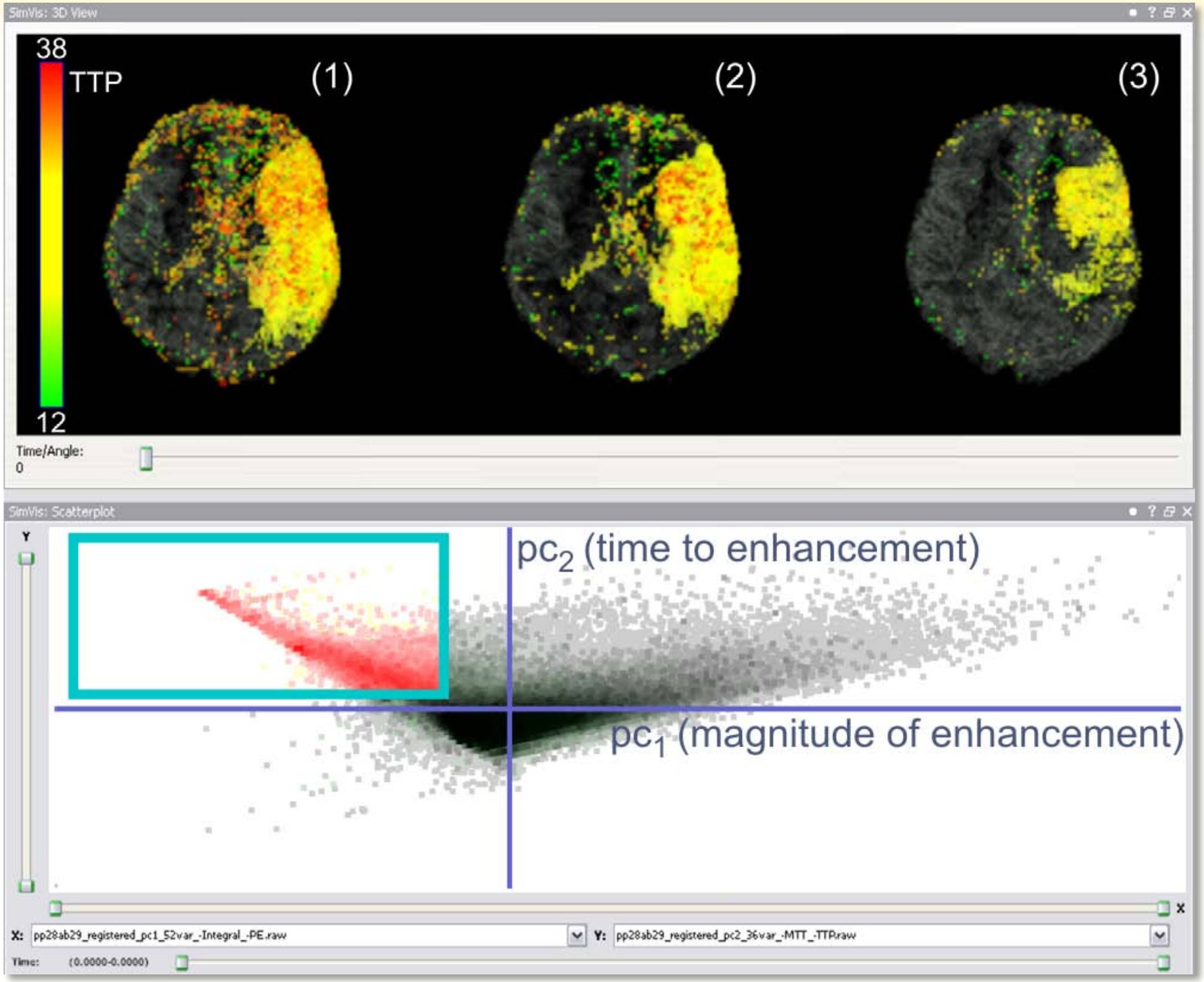
Smooth brushing and subsequent outlier removal in a parallel coordinates plot reveal ischemic tissue



Ischemic Stroke Diagnosis

Analysis based on enhancement trends

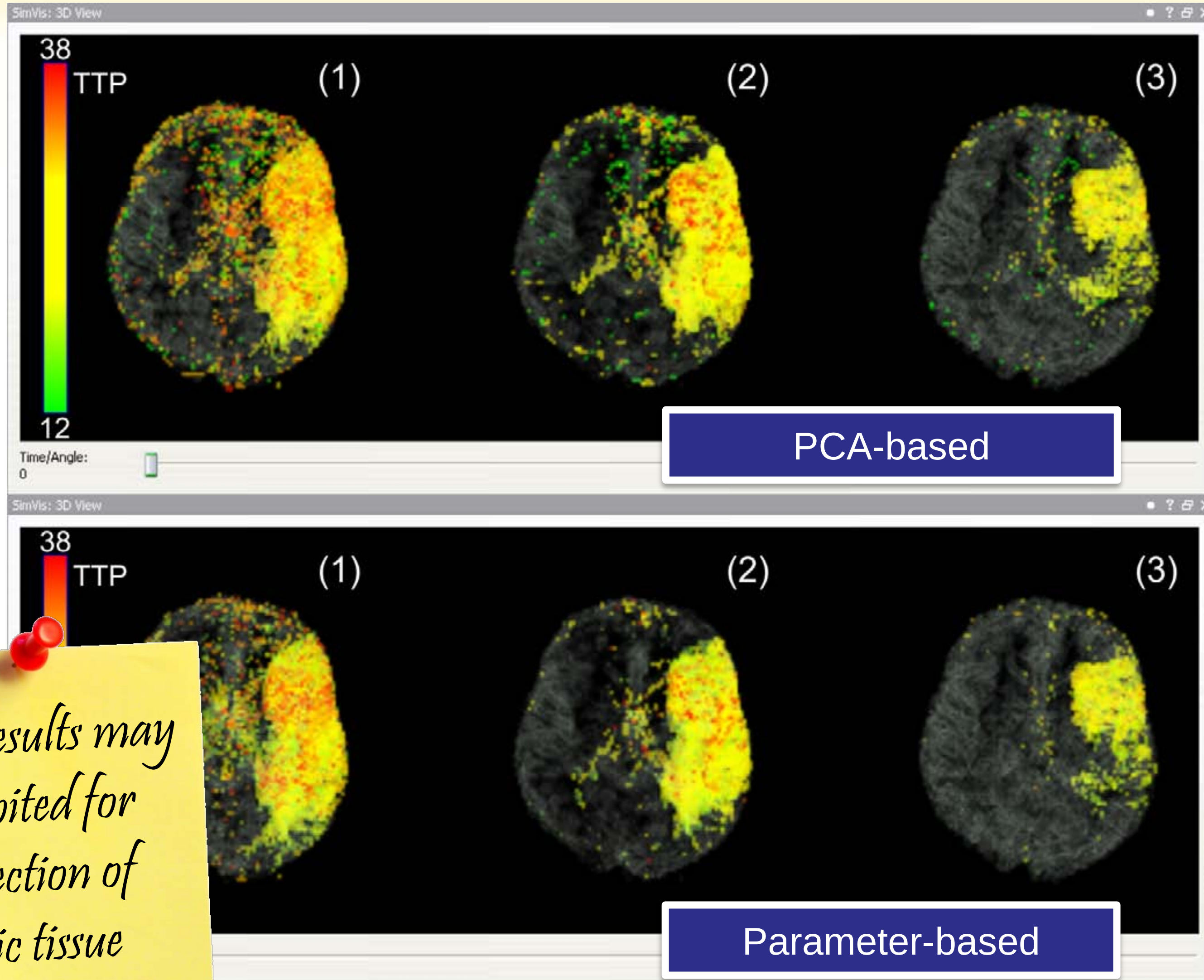
Brushing the first two principal components yields a similar result as compared to the parameter-based selection



Ischemic Stroke Diagnosis

Analysis based on enhancement trends

Brushing the first two principal components yields a similar result as compared to the parameter-based selection

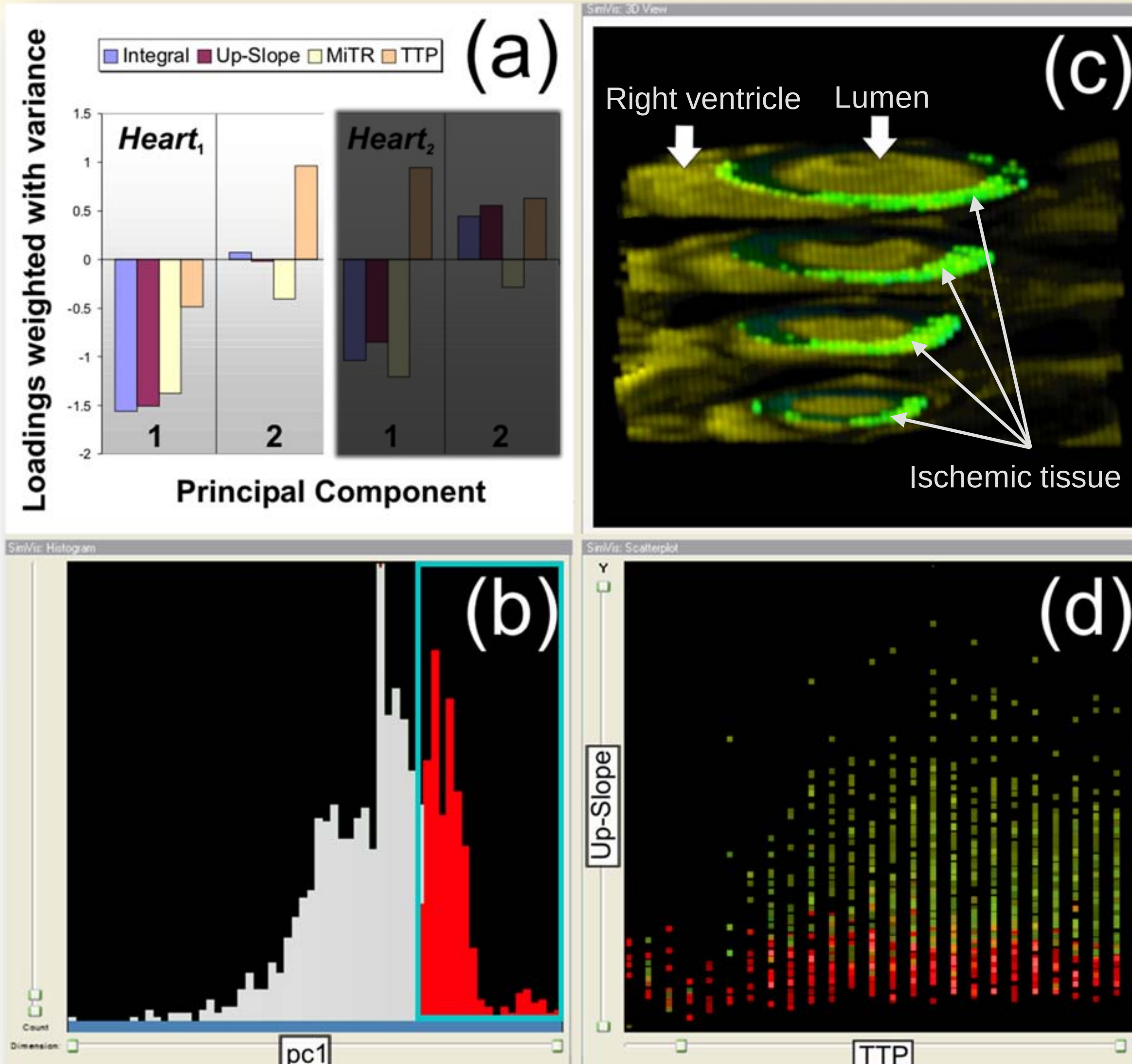


PCA results may be exploited for the detection of ischemic tissue

CHD Diagnosis

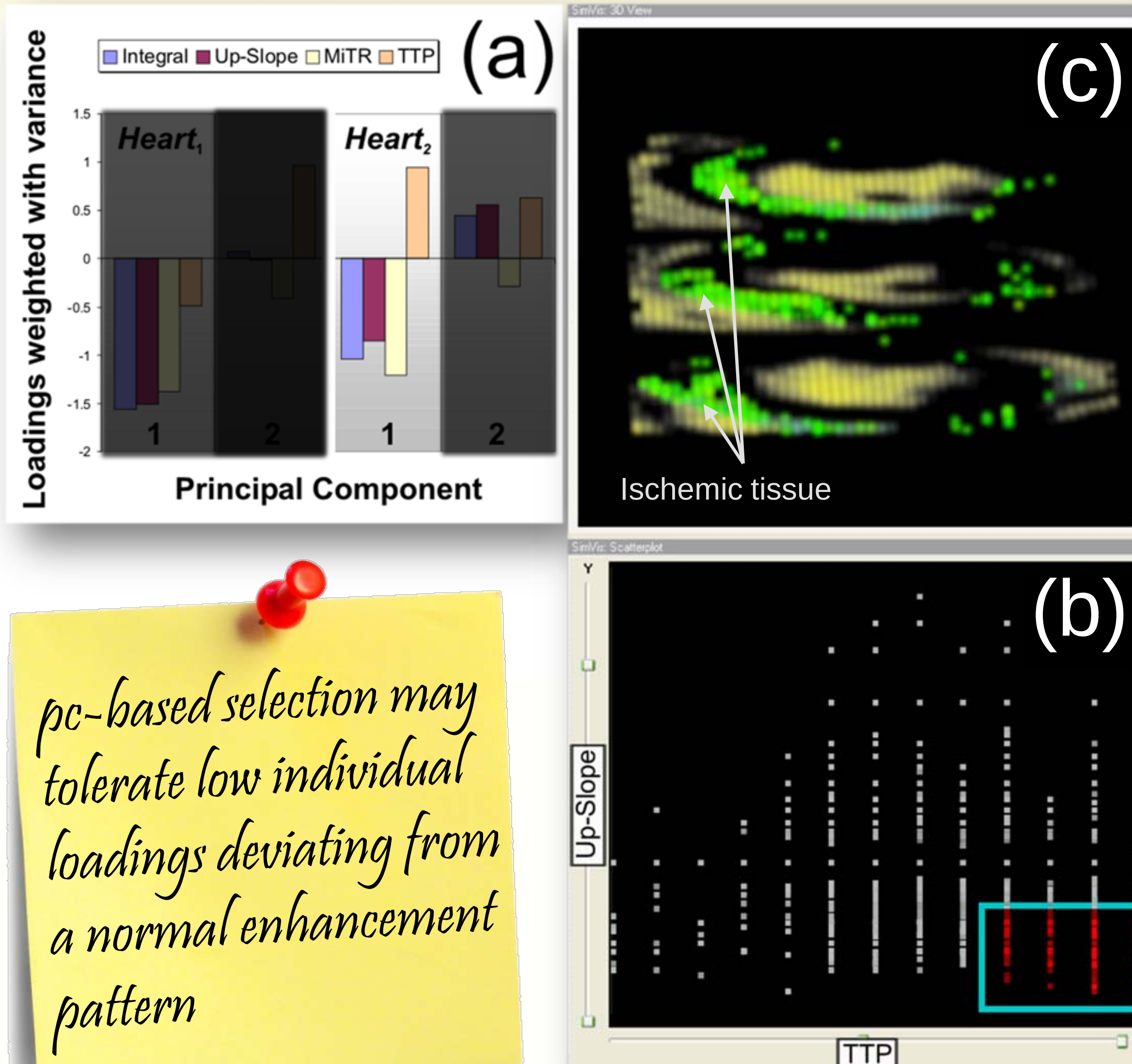
- (a) PCA results related to two datasets
- (b) Brushing high scores of *pc1* in *Heart$_1$*
- (c) Brushing reveals ischemic tissue
- (d) Transfer of brushed selection to scatter-plot (red c

- *TTP not reliable in this case*
- *Indicated by trend in pc_1*



CHD Diagnosis

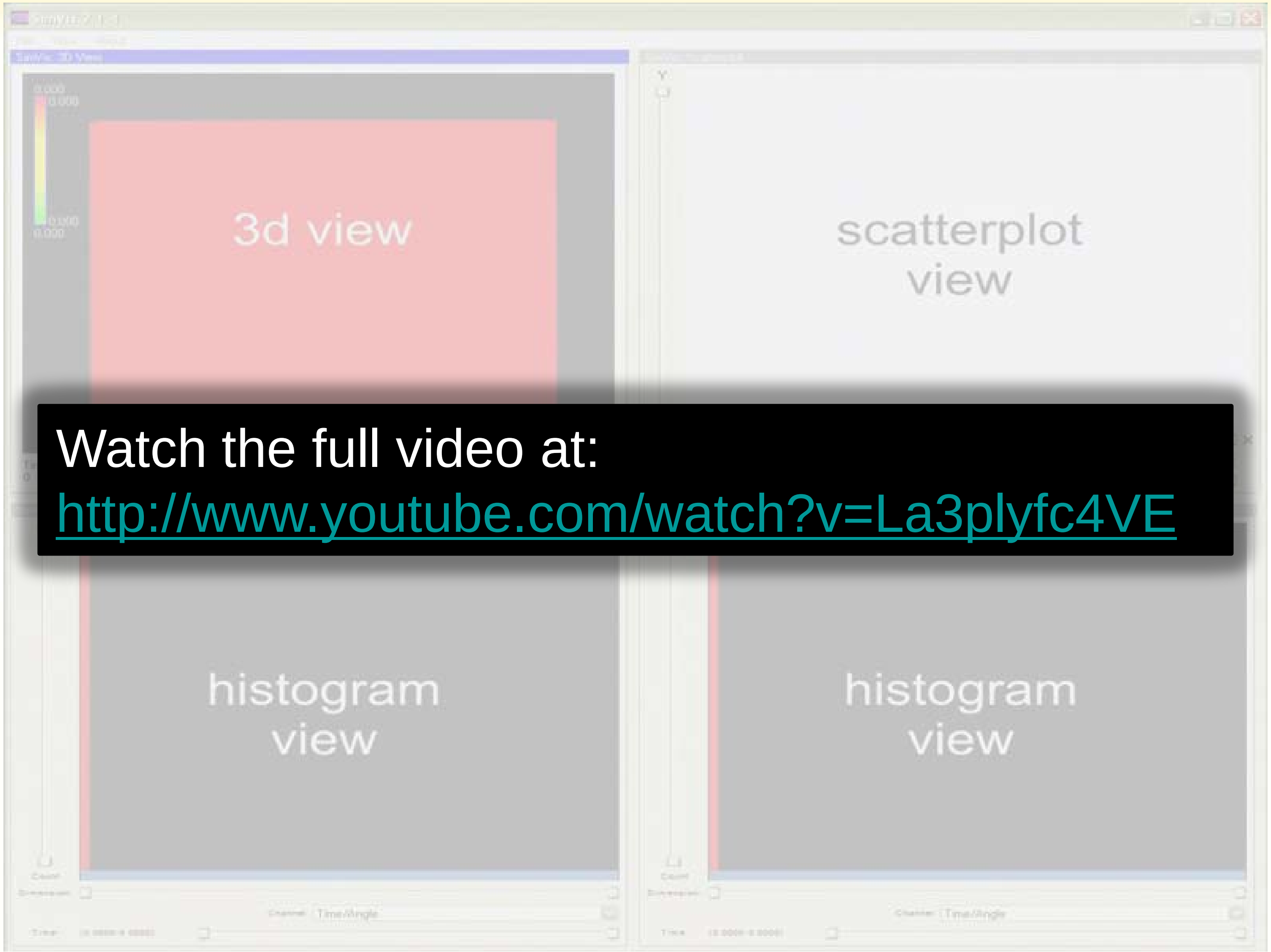
- (a) PCA results related to two datasets
- (b) Brushing parameter range representing delayed perfusion
- (c) Brushing reveals ischemic tissue



Reliability of a parameter may vary from case to case

pc-based selection may tolerate low individual loadings deviating from a normal enhancement pattern

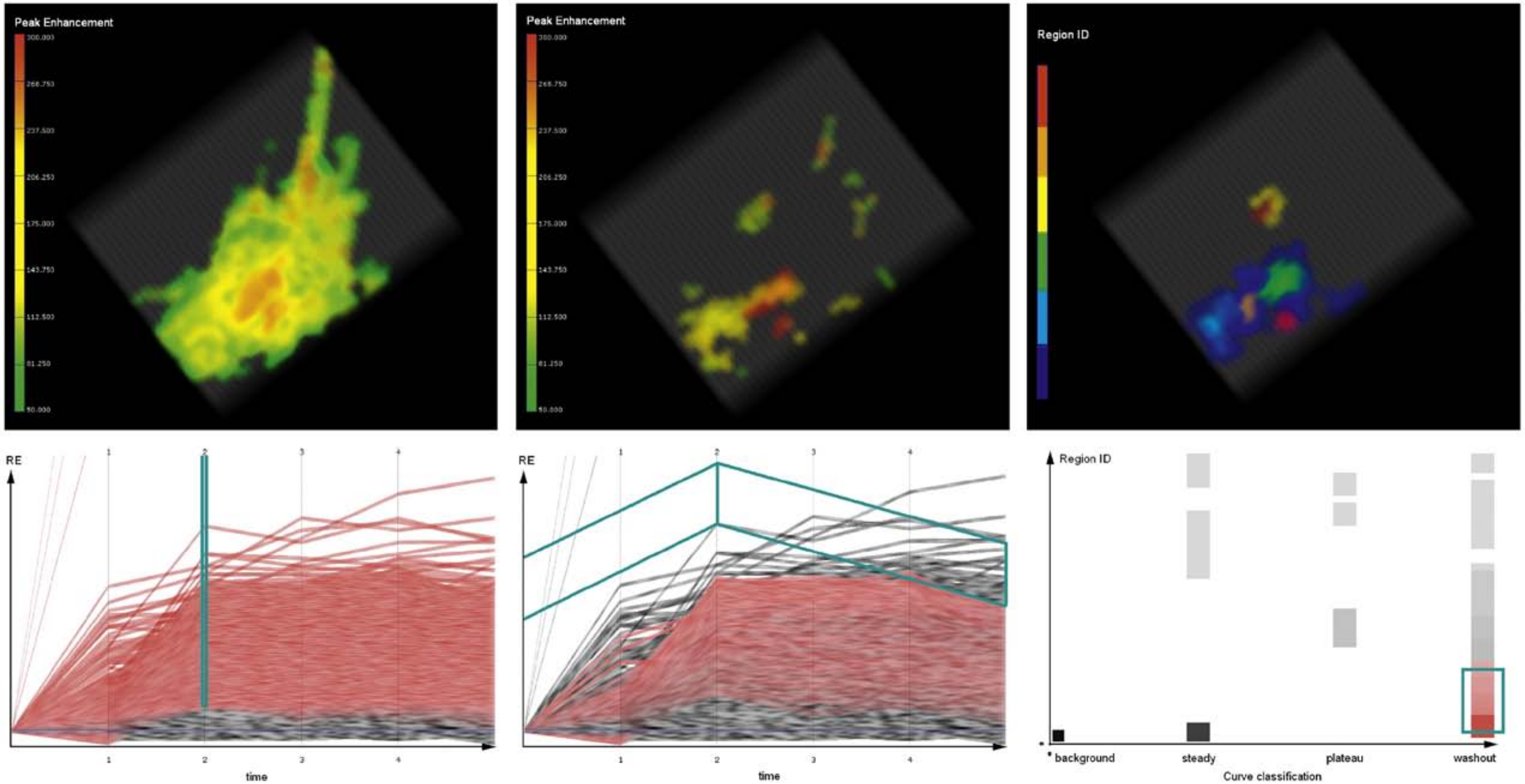
Breast Tumor Diagnosis (Video)



Watch the full video at:
http://www.youtube.com/watch?v=La3plyfc4VE

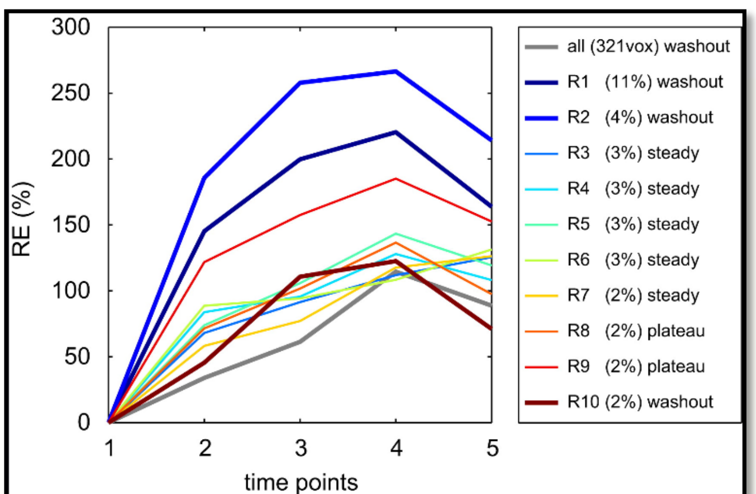
Breast Tumor Diagnosis

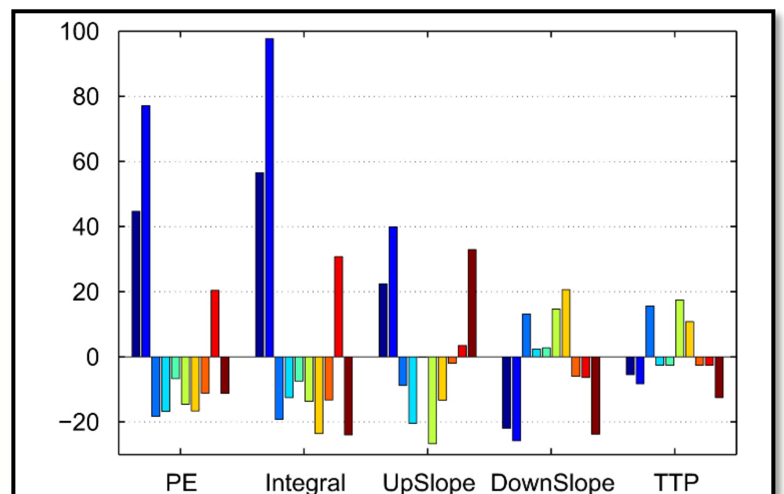
- Similarity brushing of time intensity curves for evaluating a tumor outperforms ROI-based evaluation in physical space
- User-defined ROIs may cover malignant and benign tissue



Breast Tumor Diagnosis

- Avoiding intra-observer variability by automatic, similarity-based clustering of perfusion data
- Regions with similar characteristics (time intensity curves or perfusion parameters) are merged in physical space
- Region merging considers spatial location AND attributes



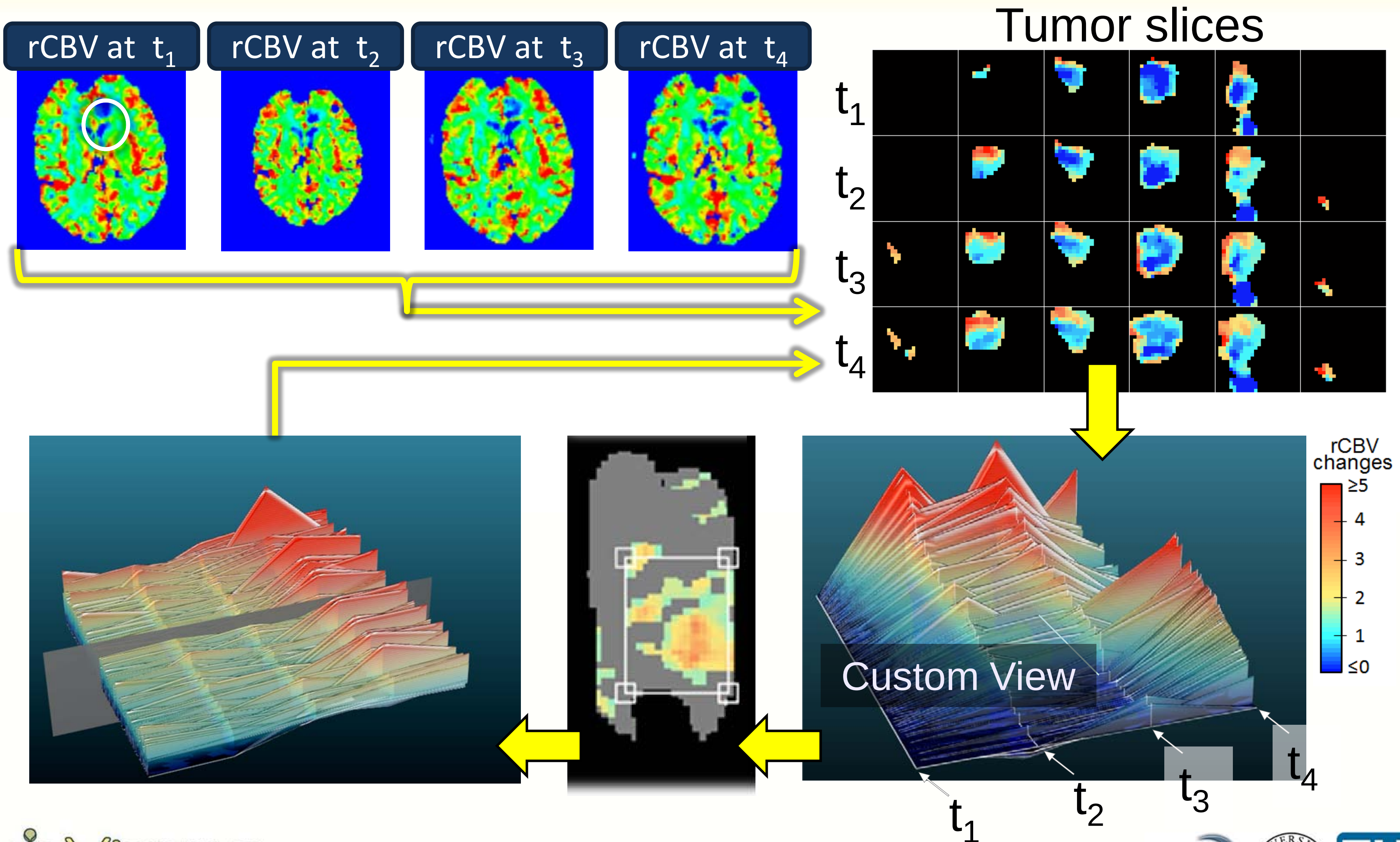


Brain Tumor Monitoring

- Gliomas are the most common brain tumors
- Vary from low to high grade gliomas (LGG/HGG)
- LGGs may transform into HGGs
- LGGs are subject to a life-long MRI monitoring if surgical removal or radiation therapy are not applicable
- Perfusion and conventional MRI for grading and monitoring
- Detecting the transformation as early as possible is crucial
- May influence the therapeutical strategy

➔ Retrospective IVA of longitudinal MRI perfusion data

Brain Tumor Monitoring



Literature

- S. Busking, C.P. Botha, F.H. Post: *Dynamic Multi-View Exploration of Shape Spaces*. Comput. Graph. Forum 29(3): 973-982 (2010)
- X. Dai, M. Gahegan: *Visualization Based Approach for Exploration of Health Data and Risk Factors*. Proc. Of 8th International Conference on GeoComputation, 2005.
- S. Glaßer, U. Preim, K.D. Tönnies, B. Preim: *A visual analytics approach to diagnosis of breast DCE-MRI data*. Computers & Graphics 34(5): 602-611 (2010)
- S. Glaßer, S. Oeltze, U. Preim, A. Bjornerud, H. Hauser, B. Preim: *Visual analysis of longitudinal brain tumor perfusion*. Proc. of SPIE Medical Imaging, 2013.
- R. Jianu, C. Demiralp, D. Laidlaw: *Exploring 3D DTI Fiber Tracts with Linked 2D Representations*. IEEE Trans. Vis. Comput. Graph. 15(6): 1449-1456 (2009)
- D.F. Keefe, M. Ewert, W. Ribarsky, R. Chang: *Interactive Coordinated Multiple-View Visualization of Biomechanical Motion Data*. IEEE Trans. Vis. Comput. Graph. 15(6): 1383-1390 (2009)
- P.R. Krekel, E.R. Valstar, J. De Groot, F.H. Post, R.G.H. H. Nelissen, C.P. Botha: *Visual Analysis of Multi-Joint Kinematic Data*. Comput. Graph. Forum 29(3): 1123-1132 (2010)
- M. König, E. Klotz, L. Heuser: *Cerebral perfusion CT: theoretical aspects, methodical implementation and clinical experience in the diagnosis of ischemic cerebral infarction*. Röfo, 172(3): 210-218 (2000)
- R. Maciejewski, R. Hafen, S. Rudolph, S.G. Larew, M.A. Mitchell, W.S. Cleveland, D.S. Ebert: *Forecasting Hotspots—A Predictive Analytics Approach*. IEEE Trans. Vis. Comput. Graph. 17(4): 440-453 (2011)
- S. Oeltze, H. Doleisch, H.Hauser, P. Muigg, B. Preim: *Interactive Visual Analysis of Perfusion Data*. IEEE Trans. Vis. Comput. Graph. 13(6): 1392-1399 (2007)
- S. Oeltze, H. Hauser, J. Rorvik, A. Lundervold, B. Preim: *Visual Analysis of Cerebral Perfusion Data -- Four Interactive Approaches and a Comparison*. Proc. of ISPA (588-595), 2009
- B. Preim, S. Oeltze, M. Mlejnek, E. Gröller, A. Hennemuth, S. Behrens: *Survey of the Visual Exploration and Analysis of Perfusion Data*. IEEE Trans. Vis. Comput. Graph. 15(2): 205-220 (2009)
- U. Preim, S. Glaßer, B. Preim, F. Fischbach, J. Ricke: Computer-aided diagnosis in breast DCE-MRI--quantification of the heterogeneity of breast lesions. Eur J Radiol 81(7): 532-538 (2011)

Literature

- A.F. van Dixhoorn, B.H. Vissers, L. Ferrarini, J. Milles, C.P. Botha: *Visual Analysis of Integrated Resting State Functional Brain Connectivity and Anatomy*. Proc. of VCBM (57-64), 2010
- H. Völzke et al.: *Cohort profile: the study of health in Pomerania*. Int J Epidemiol. 40(2): 294-307 (2011)
- T.D. Wang, K. Wongsuphasawat, C. Plaisant, B. Shneiderman: *Extracting insights from electronic health records: case studies, a visual analytics process model, and design recommendations*. J Med Syst. 35(5): 1135-52 (2011)
- S. Zachow, P. Muigg, T. Hildebrandt, H. Doleisch, H.-C. Hege*: Visual exploration of nasal airflow*. IEEE Trans. Vis. Comput. Graph. 15(6): 1407-1414 (2009)

Enjoy your break ☺

…and come back.