Graph Analysis of Brain Networks

Time Series Analysis and Pattern Mining of Dynamic Neuroimaging Data

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Outline

1. **Vision Restoration**

   Stimulation-induced Synchronization by rtACS

2. **Brain Connectivity**

3. **Data Mining**

4. **Model-based Analysis of Dynamic Brain Networks**

5. **Periodic Subgraph Mining**

6. **Conclusions and Future Work**

Visual Loss is the Most Feared Disease
in the Elderly

tunnel vision

hemianopia

- 19% of persons $> 70\,\mathrm{yrs}$ have visual impairments
- causes:
  - age-related macular degeneration (AMD)
  - glaucoma
  - diabetic retinopathy
  - stroke and trauma
  - optic nerve damage
  - retinitis pigmentosa

Schematic Overview of Visual Field Defects

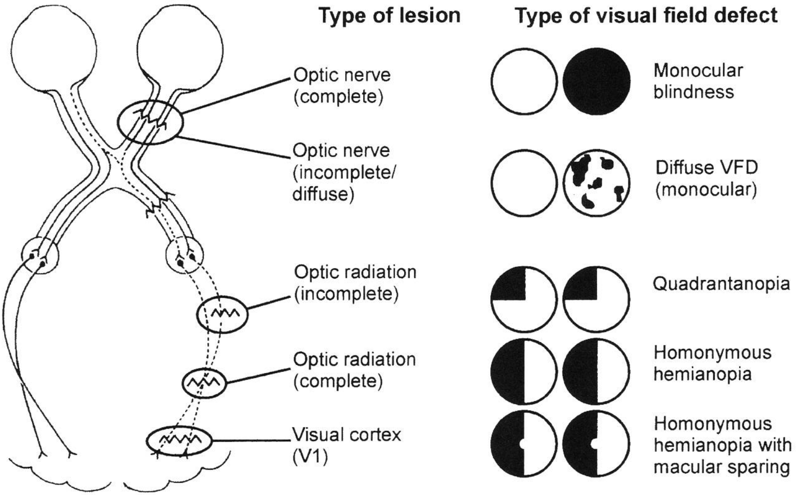
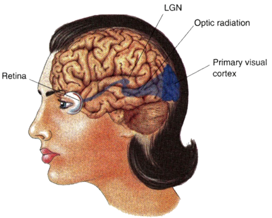
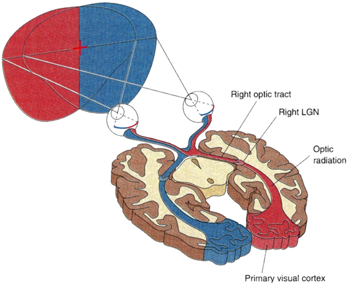


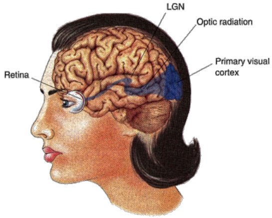
Fig. 1. Schematic overview of visual field defects (white = intact, black = blind areas) which result from lesions at different locations of the visual system.

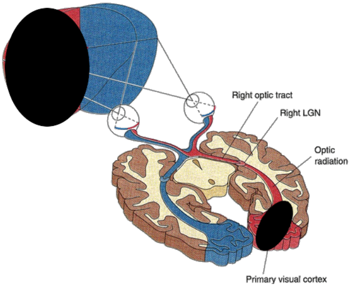
Visual Pathway

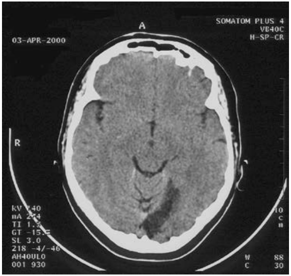




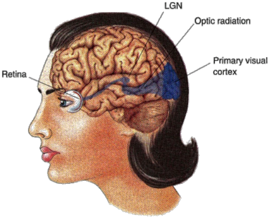
Low Vision after Brain Damage

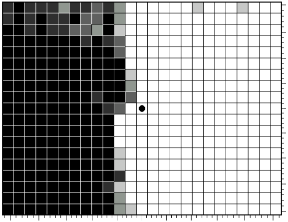


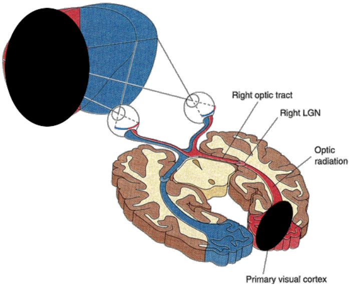


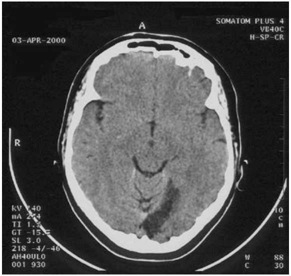


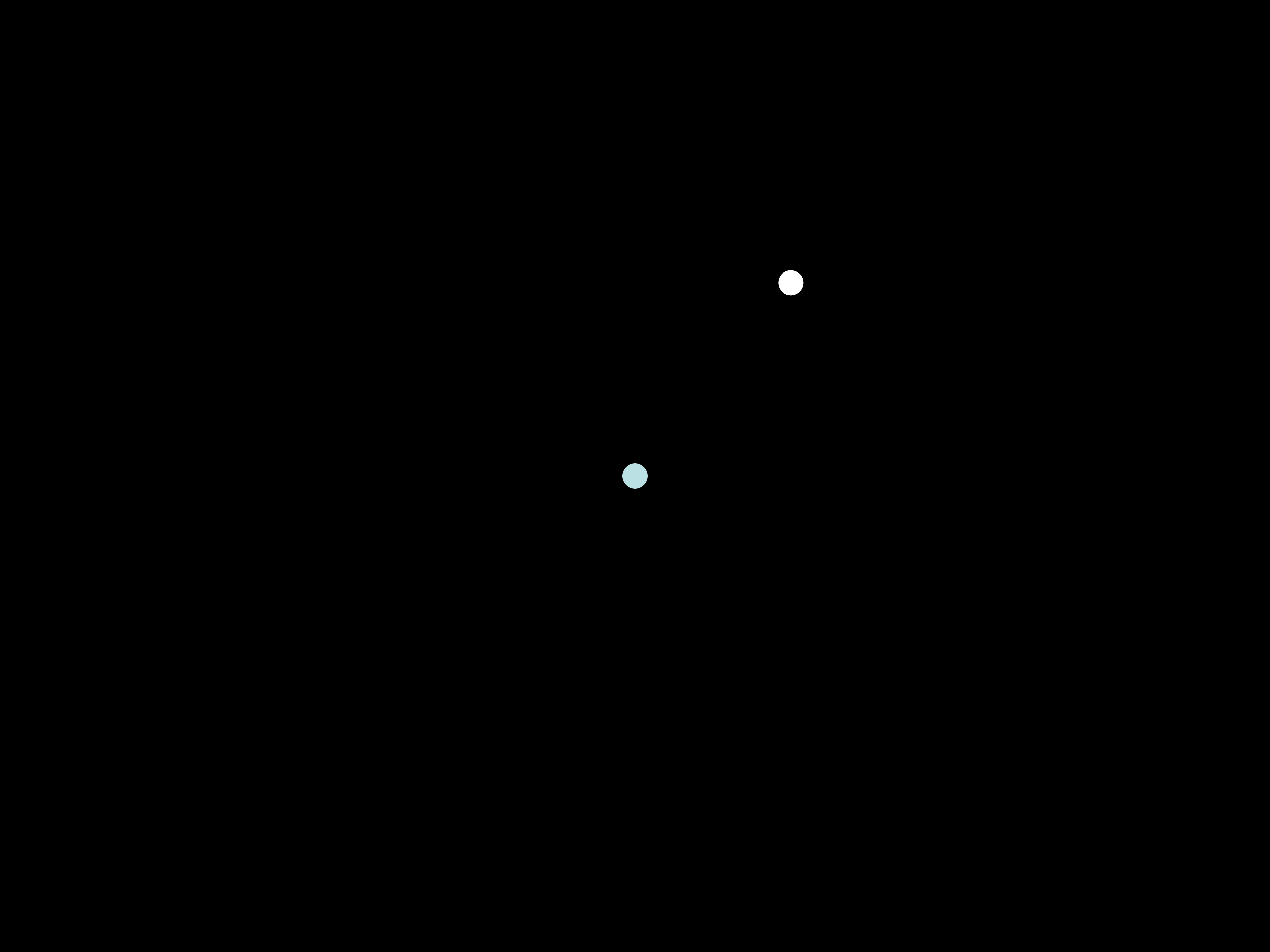
Low Vision after Brain Damage

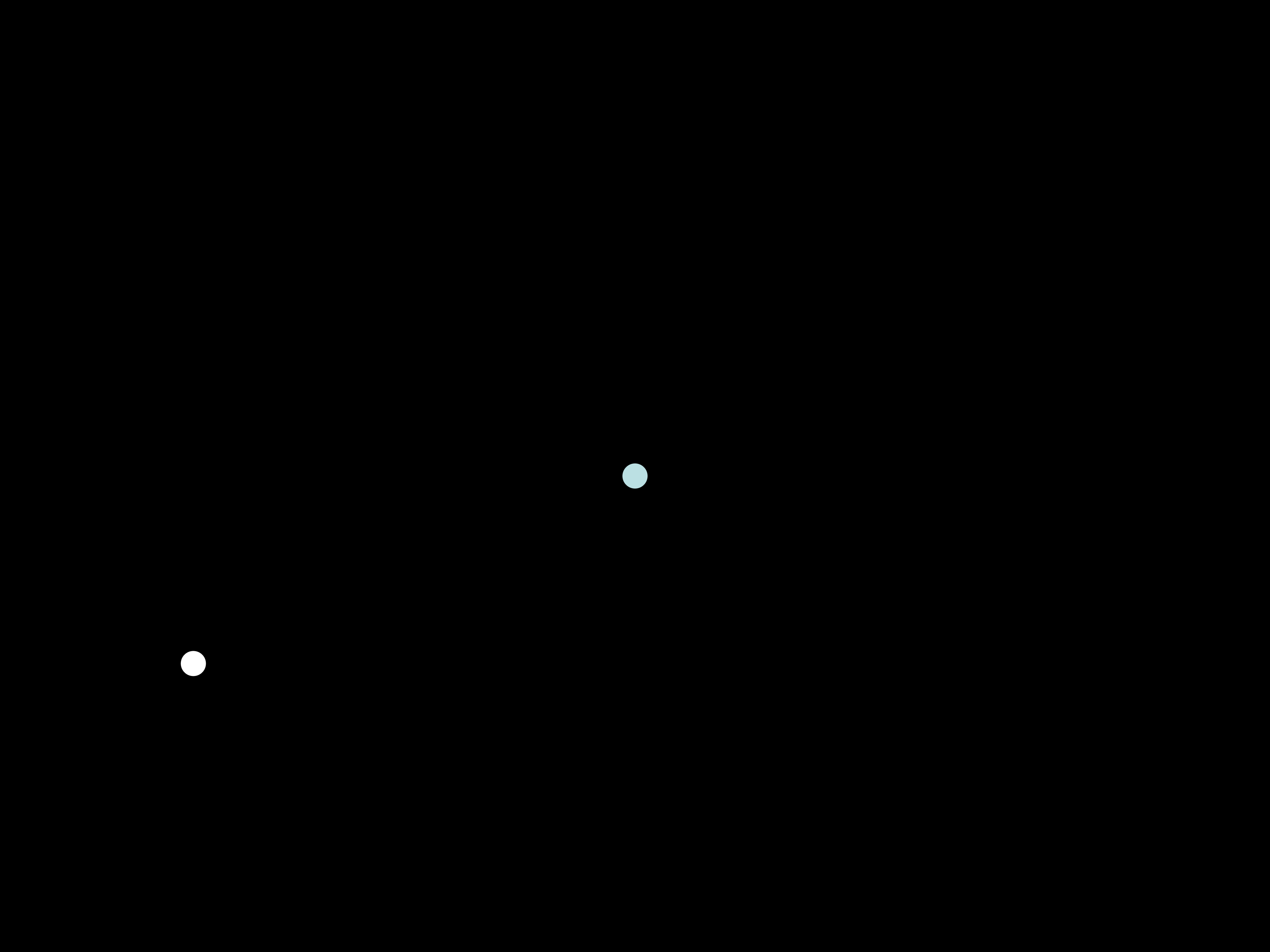




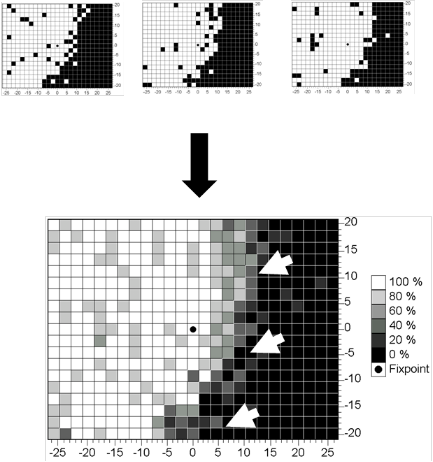


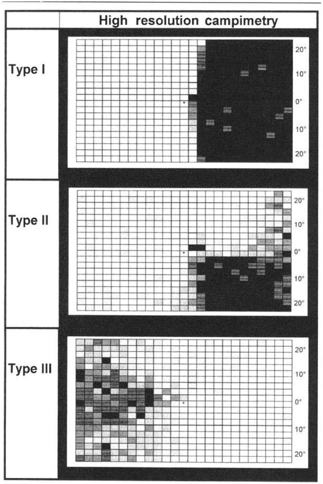






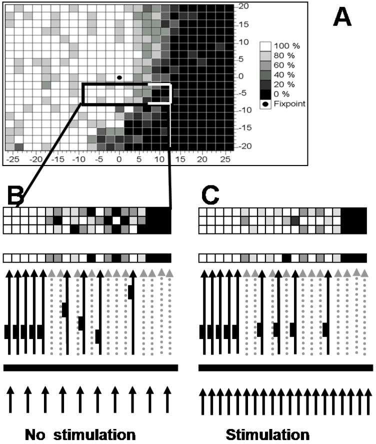
Visualization of Residual Functions

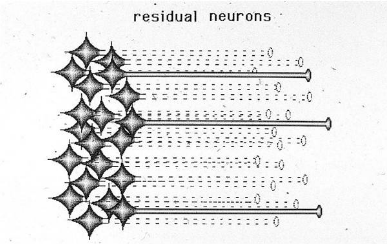




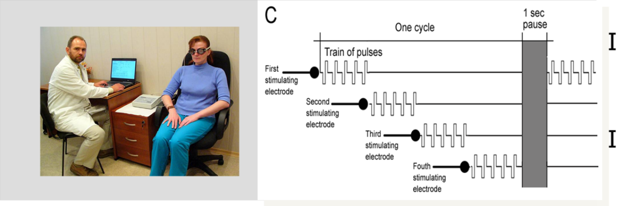
Superimposed evaluations of the central visual field (± 25° eccentricity) using high resolution perimetry. Different types of transition zones have been found. (Upper panel) Sharp visual field border, and, accordingly, a small transition zone. (Middle panel) Transition zone of medium extension. (Lower panel) Fuzzy border, large transition zones, with scattered visual field defects. Black, blind areas; gray, areas of relative defects, *ie*, transition zones with residual vision; white, intact

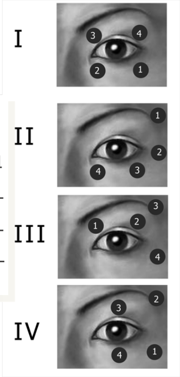
Stimulation-induced Synchronization





Repetitive Transorbital AC Stimulation (rtACS)

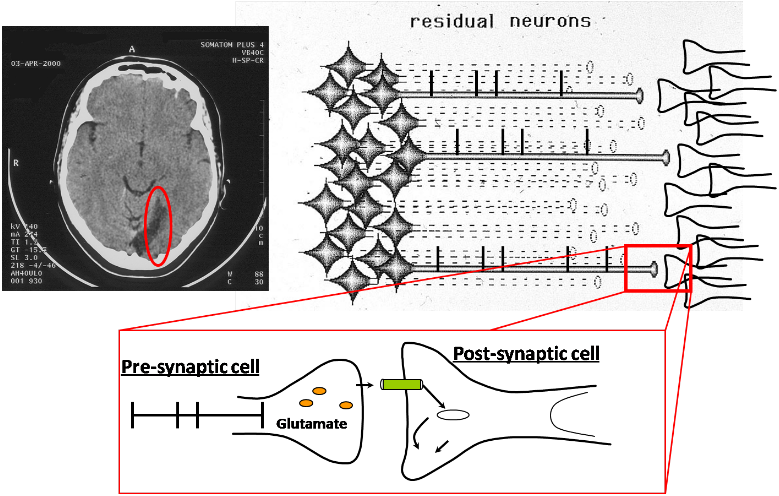




- placing non-invasive electrodes at eye or skull
- rtACS with low current stimulation ($< 1\,\mathrm{mA}$, $10 - 30\,\mathrm{Hz}$)
- 20-40 min daily for approx. 10 days

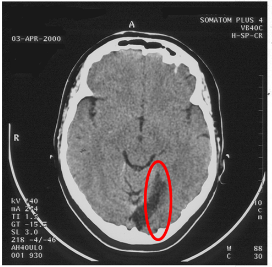
Synaptic Transmission after Partial Damage

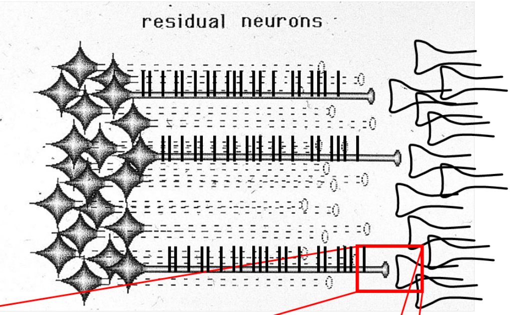
Before rtACS

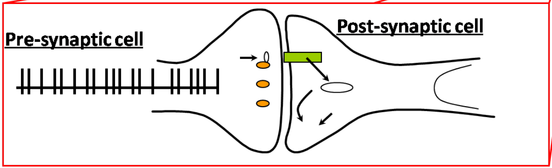


Synaptic Transmission after Partial Damage

After rtACS

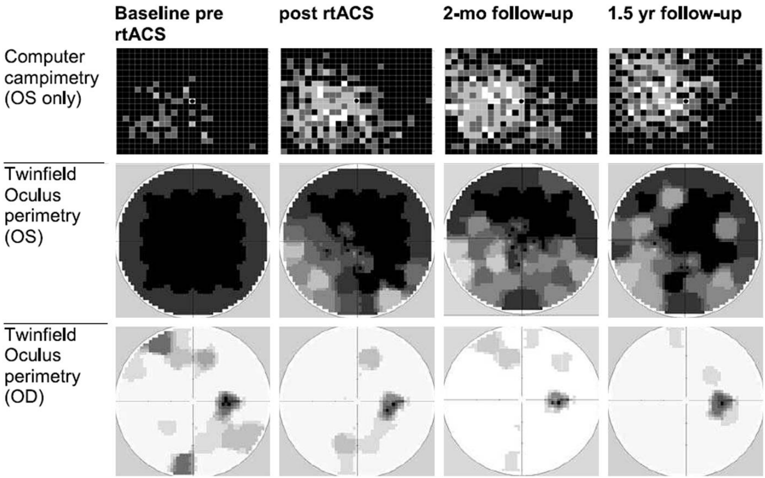






Goal: strengthening synaptic transmission

Visual Fields in Optic Nerve Lesion after rtACS



Challenge: Electroencephalogram (EEG)

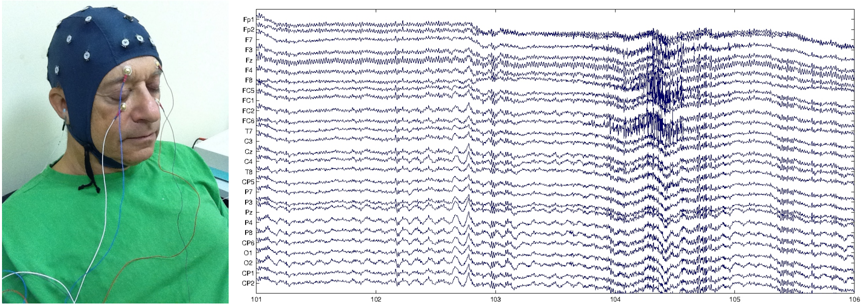


Figure: Left: Vision restoration therapy using alternating current. Right: Typical raw data (28 EEG channel).

- 25 subjects: each EEG has been filtered by common filters
- **hypothesis:** pairwise channel similarity contains useful information (Sporns 2010)

Scope and Goal of my Work

- scope: complex networks in real-world applications
- status quo: data mining and network theory studied separately
- research goal: interdisciplinary research by combining techniques
- focus: analysis of dynamic neuroimaging networks
- applications: clinical decision support systems, exploration of dynamic in complex networks

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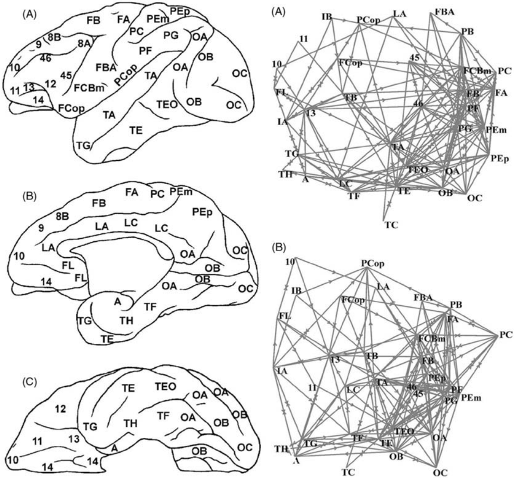
1. Vision Restoration
2. **Brain Connectivity**
3. Data Mining
4. Model-based Analysis of Dynamic Brain Networks
5. Periodic Subgraph Mining
6. Conclusions and Future Work

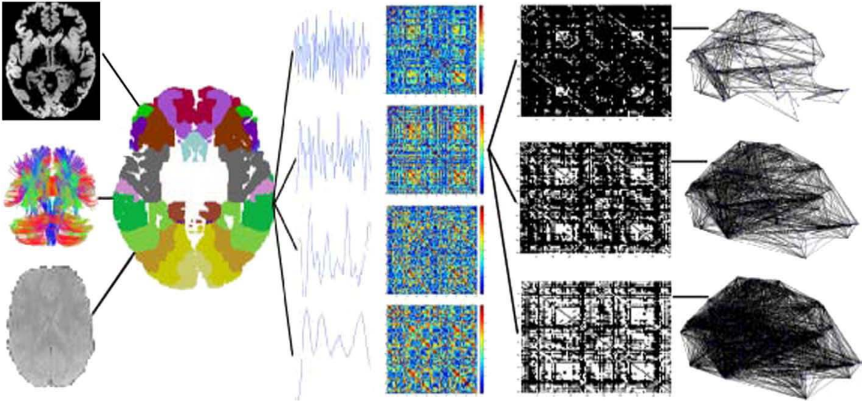
Cortical Connectivity Maps

Stephan et al. 2000

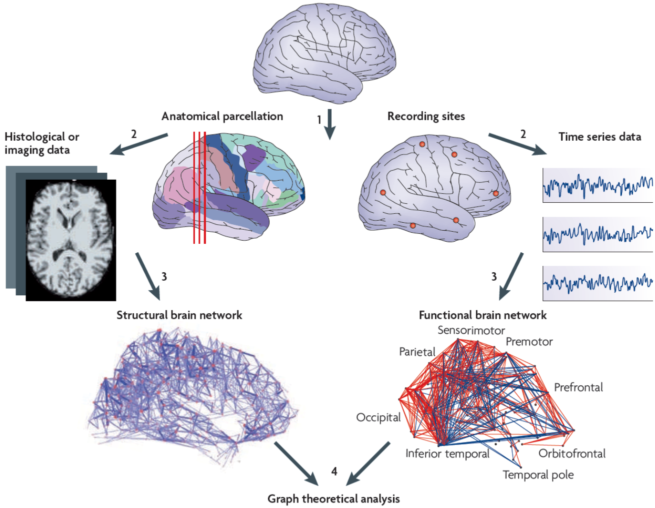


fMRI Graphs

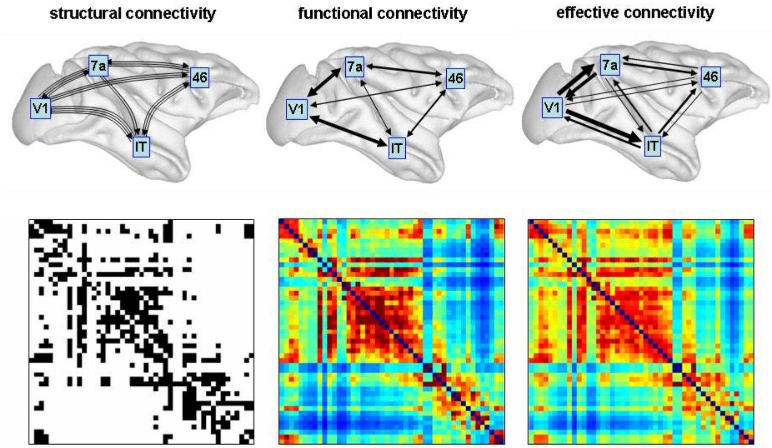
Bullmore, Barnes, et al. 2009



Brain Network Analysis
Bullmore and Sporns 2009



Brain Connectivity
Sporns 2007



- anatomical links vs. statistical dependencies vs. causal interactions

Outline

1. Vision Restoration

2. Brain Connectivity

3. **Data Mining**
   - Knowledge Discovery in Databases
   - CRISP-DM

4. Model-based Analysis of Dynamic Brain Networks

5. Periodic Subgraph Mining

6. Conclusions and Future Work

Data

- today: companies/institutes maintain huge databases

⇒ gigantic archives of tables, documents, images, sounds

- *“If you have enough data, you can solve any problem!”*
- in large databases: can’t see the wood for the trees
- patterns, structures, regularities stay undetected
- finding patterns and exploit information is fairly difficult

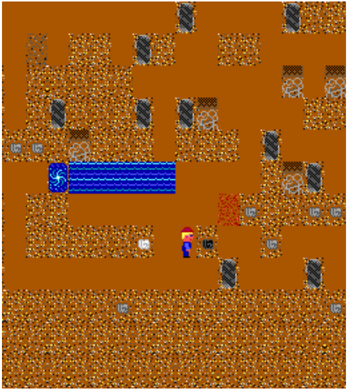
We are drowning in information but starved for knowledge. *[John Naisbitt]*

Knowledge Discovery in Databases

- actually, abundance of data
- lack of tools transforming data into knowledge

⇒ research area: knowledge discovery in databases (KDD)

- nontrivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data
- one step in KDD: data mining



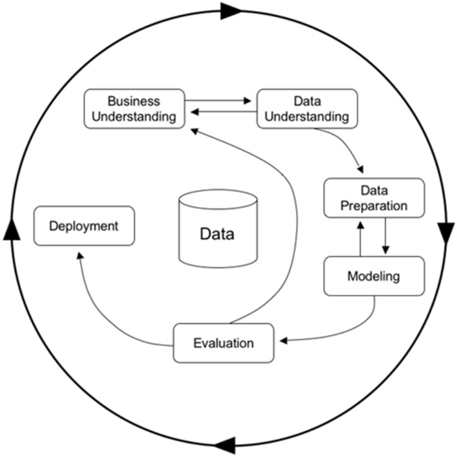
Miner VGA (1989) screenshot

Data Mining Tasks

- classification
  Is this patient a responder or non-responder?
- segmentation, clustering
  What groups of patients do I have?
- concept description
  Which properties characterize verum patients?
- prediction
  How much will the patient improve his/her vision?
  Which current and frequency must be applied?
- dependence/association analysis
  Which EEG waves of verum patients occur together frequently?

CRISP-DM

CRoss Industry Standard Process for Data Mining



Outlook: Find Frequent Patterns in Raw EEG

Which EEG waves occur together frequently?

- every wave = shopping item
- EEG recording = market basket
- frequent patterns = frequent item sets
- association rule learning

Outline

EEG Similarity: Synchronization likelihood

Stam and Dijk (2002); Montez et al. (2006)

time-delay embedding: $X_{i,k} = \left(x_{i,k}, x_{i+L,k}, x_{i+2\cdot L,k}, \ldots, x_{i+(m-1)\cdot L,k}\right)$

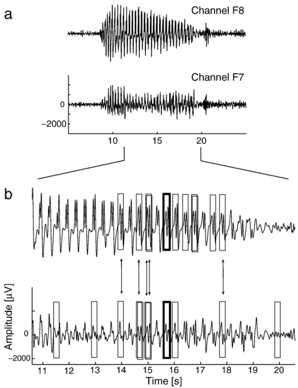
- consider only 2 channels A, B
- probability that $X_{i,k} \leq \varepsilon$:

$$P^{\varepsilon}_{i,k} = \frac{1}{2(W_2 - W_1)} \sum_{\substack{j \\ W_1 < |i-j| W_2}}^{N} \theta(\varepsilon - d(X_{i,k}, X_{j,k}))$$

$$H_{i,j} = \theta(\varepsilon_{i,A} - d(X_{i,A}, X_{j,A})) + \theta(\varepsilon_{i,B} - d(X_{i,B}, X_{j,B}))$$

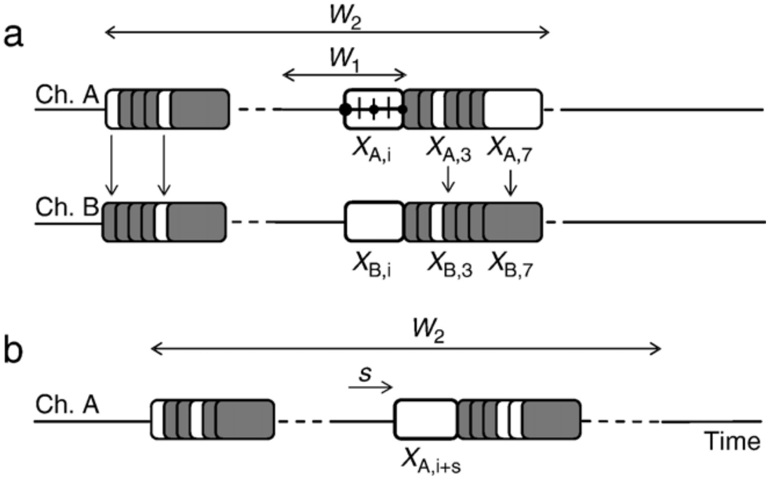
$$SL_i = \frac{1}{2p_{\mathrm{ref}}(W_2 - W1)} \sum_{\substack{j \\ W_1 < |i-j| W_2}}^{N} (H_{i,j} - 1)$$

- parameters m, L, W_1, W_2, p_{ref} can be estimated

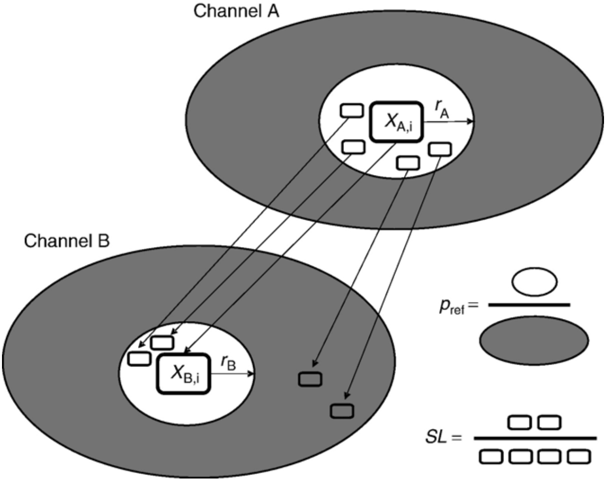


State Vectors and SL Parameters

Montez et al. (2006)



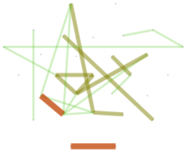
SL of 2 Channels
Montez et al. (ibid.)



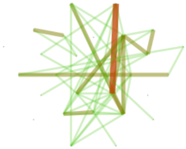
From EEG to Dynamic Graphs

δ: deep sleep

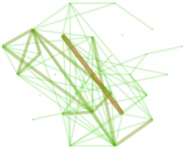
θ: drowsiness/arousal



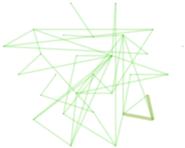
α: relaxed/reflecting



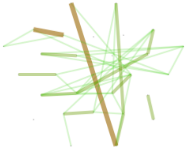
β: alert/working



γ: cognitive functions



μ: RS motor function



- dynamic graphs of common human EEG frequency bands
- edge width/color represents SL $\in [0, 1]$

Dynamic Graphs

Q: What can change over time?

A: Everything ;-)

four categories (Harary and Gupta 1997):

- vertex-dynamic graph: vertices can be added/removed
- edge-dynamic graph: edges can be added/deleted
- vertex weighted dynamic graph: weights on vertices can change
- *edge weighted dynamic graph:* edge weights can change

needed: informative graph measures

Graph Measures
(Steen 2010)

- *degree* of $v \in V$: $\delta(v) \stackrel{\text{def}}{=} |N(v)|$
  for weighted G: $\delta(v) \stackrel{\text{def}}{=} \sum_{u \in N(v)} w(\langle u, v \rangle)$
- $g_{u \leftrightarrow v}$: shortest path (geodesic) between u, v
- *distance* d between u, v: $d(u, v) \stackrel{\text{def}}{=} \sum_{e \in g_{u \leftrightarrow v}} w(e)$
- *diameter* $\varnothing(G) = \max_{u,v \in V(G)} d(u, v)$

Graph Measures
(Latora and Marchiori 2001)

- efficiency of vertex u:

$$\eta(u) = \sum_{v \in V, v \neq u} {}^{1}/_{d(u,v)}$$

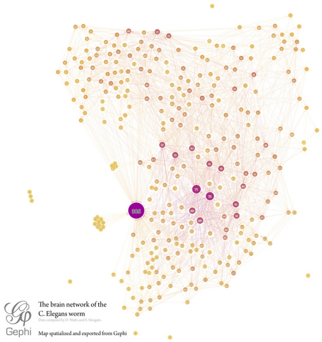
- *global efficiency* of G:

$$\bar{\eta}(G) \stackrel{\text{def}}{=} \frac{1}{|V|} \sum_{u \in V} \eta(u)$$

- *local efficiency* of G:

$$\bar{\eta}_{\text{loc}}(G) \stackrel{\text{def}}{=} \frac{1}{|V|} \sum_{u \in V} \bar{\eta}(G[\{u\} \cup N(u)])$$

Neural Networks of C. Elegans
(Watts and Strogatz 1998)



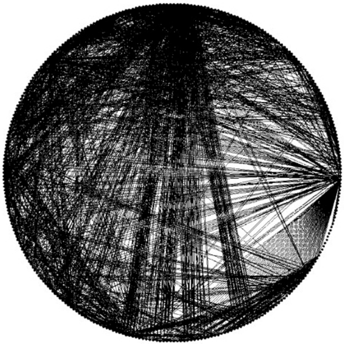
source: http://www.flickr.com/photos/gephi/

source: http://blog.neuinfo.org

- *Caenorhabditis elegans*
- 302 neurons, approx. 7.000 synapses
- Sydney Brenner (Nobel Prize in Medicine 2002)

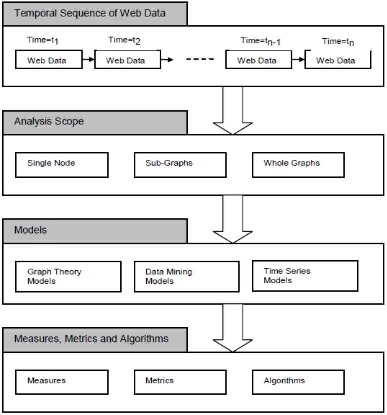
Example: C. elegans

(ibid.)



	d_{actual}	d_{random}	c_{actual}	c_{random}
C. elegans	2.65	2.25	0.28	0.05

Dynamic Graph Analysis

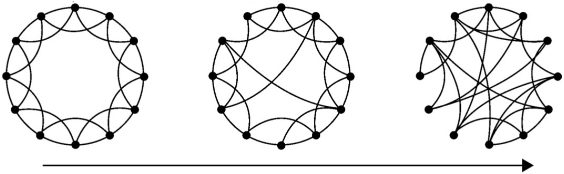


source: (Desikan and Srivastava 2004)

- ARMA models of graphs: anomaly detection (Pincombe 2005), feature selection (Moewes, Kruse, et al. 2012)
- VAR models of graphs: feature selection (Moewes and Kruse 2012)

Graph Models
(Erdős and Rényi 1960)

regular	small-world	random
high L, high C	low L, high C	low L, low C



increasingly random connectivity

- edge is added with prob. p independently from other edge
- graphs with n vertices and m edges have equal probability of

$$p^m(1-p)^{\binom{n}{2}-m}$$

- algorithmic models to construct graphs: (Watts and Strogatz 1998) and (Barabási and Albert 1999)

Time Series Model for Graph Measures

goal: find coherence between dynamic functional networks and clinical variables from patients with visual field defects

- networks have been created by synchronization likelihood

$\Rightarrow$ series of weighted networks

- every graph was described by several graph measures

$\Rightarrow$ time series of graph measures

- fitted time series model for each patient
- model parameters have been correlated to clinical variables

(Vector) Autoregressive Model

Box, Jenkins, Reinsel (2008)

AR(p) model

$$x_t = \epsilon_t + \sum_{i=1}^{p} a_i x_{t-i}$$

multivariate case: VAR(p)

$$\vec{x}_t = \vec{c} + \sum_{i=1}^{p} A_i \vec{x}_{t-i} + \vec{\epsilon}_t$$

Example: Time Series of Graph Measures

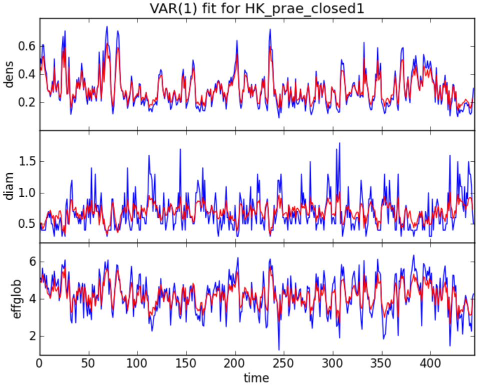


Figure: Blue: Original graph measures. Red: Fitted graph measures.

measures for VAR(1) model: density, global efficiency, diameter

Experiment

given:

- VAR models for each subject (and for each frequency band)
- 6 clinical variables

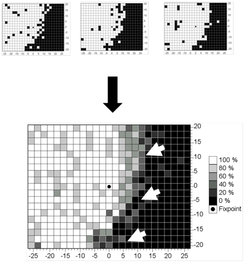
goal:

- VAR coefficients $\leftrightarrow$ clinical variables
- *e.g.* linear regression
- here, ridge regression with $\alpha \in [0.1, 0.2, \ldots, 0.9, 1]$
- parameter search: leave-one-out cross-validation

Results

evaluated by score coefficient

$$R^2 = 1 - \frac{\text{MSE}}{res}$$



whereas MSE $= \sum_{i=1}^{n}(x_i - x_i')^2$ and res $= \sum_{i=1}^{n}(x_i - \bar{x})^2$
best score $R^2 = 1$ (the lower, the worse)

variable	δ	θ	α	β	γ	μ
# white	.198	.727	.715	.276	.207	.370
# gray	.193	.101	.156	.240	.273	.189
# black	.226	.605	.692	.328	.269	.400
# white (CMF)	.179	.698	.608	.288	.232	.338
# gray (CMF)	.177	.105	.183	.446	.185	.226
# black (CMF)	.206	.630	.696	.311	.273	.364

Summary

- still unknown: whether EEG features can describe damages of human visual system
- goal of this study: find suitable network measures and clinical features
- static analysis (Held et al. 2012), dynamic analysis (Moewes, Kruse, et al. 2012)
- most informative frequency bands: δ and αband
- most informative clinical variables: proportion of intact and absolutely defected sectors
- features will be used in future work

Outline

Periodic Subgraph Mining

Lahiri and Berger-Wolf (2010)

- periodic subgraph mining: discovery of all interactions that occur at regular intervals in dynamic networks
- interactions occur at discrete instances over period of time
- objects of interest: graph edges and how they change over time
- focus: finding periodically occurring interaction patterns in dynamic networks

Approach

- synthesis of two different data mining problems:
  - frequent pattern mining in transactional DB
  - periodic pattern mining in *n*-dimensional sequence
- combination characterizes periodic behavior in dynamic networks

Some Definitions

- dynamic network $\mathcal{G}$ of T points in time
- for arbitrary graph $F = (V, E)$, its support set $S(F)$ in $\mathcal{G}$ is set of points in time t in $\mathcal{G}$ where F is subgraph of G_t, $F \subseteq G_t$
- *support* of F is cardinality of its support set, $|S(F)|$:

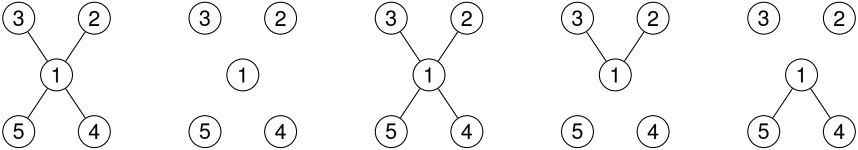
$$S(F) = \{t_i, \ldots, t_j\} \text{ s.t. } \forall (t \in S(F) \Leftrightarrow F \subseteq G_t)$$

- F is *frequent* subgraph of $\mathcal{G}$ if $|S(F)| \geq \sigma$ where $1 \leq \sigma \leq T$
- $F(\sigma)$ is set of all frequent subgraphs at minimum support σ

Maximal and Closed Subgraphs

- subgraph is *maximal* if there is no subgraph that can be derived from it
- subgraph $F \in F(\sigma)$ is *closed* if it is maximal at some support $\sigma' > \sigma$
- closed and maximal subgraphs reduce size of $F(\sigma)$

Frequent and Periodic Subgraphs



(a) $t = 1$ **(b)** $t = 2$ **(c)** $t = 3$ **(d)** $t = 4$ **(e)** $t = 5$

Figure: using $\sigma = 3$,
$\{(1,2),(1,3)\}$ is frequent but not periodic while $\{(1,4),(1,5)\}$ is both

Periodic Subgraph Embedding

- *PSE* of arbitrary subgraph $F \subseteq \mathcal{G}$ is maximal, ordered set of points in time *s.t.* difference between points in time is constant

$$S_P(F) = \langle t : F \subseteq G_t \rangle \text{ whereas } \forall i : t_{i+1} - t_i = p$$

- p is period of F whereas F is periodic subgraph $|S_P(F)| \geq \sigma$
- every subgraph can have multiple periodic embeddings in $\mathcal{G}$ with different positions, supports, etc.
- overlap can exist as long as support set is maximal

Noisy Subgraphs

- noisy subgraph has some jitter for given period
- given jitter value of $J \geq 0$

$$S_P(F) = \langle t : F \subseteq G_t \rangle \text{ whereas } \forall i : |t_{+1} - t_i - p| \leq J$$

Purity Measure

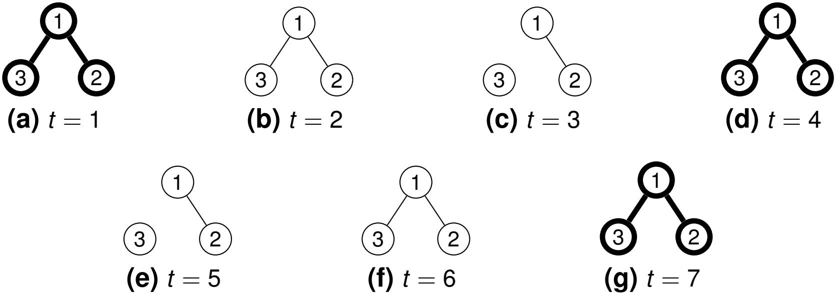
- periodically recurring subgraph does not fully represent interaction pattern that occurs periodically
- *purity measure*: how likely does periodic subgraph embedding occur within its periodically predictable point in time
- ratio of periodic support to total support in $[i, i + p(s-1)]$

$$\text{purity}(F) = \frac{s}{|\{t : F \subseteq G_t, i \leq t \leq i + p(s-1)\}|}$$

- given subgraph $F = (V, E)$, average purity

$$\text{avgPurity}(F) = \frac{1}{|E|} \sum_{e \in E} \text{purity}(e)$$

Purity Measure



(a) $t = 1$ **(b)** $t = 2$ **(c)** $t = 3$ **(d)** $t = 4$

(e) $t = 5$ **(f)** $t = 6$ **(g)** $t = 7$

Figure: periodic subgraph embedding with non-periodic occurrences, purity = $^3/_5$, average purity = $^1/_2(^3/_7 + ^3/_5) \approx 0.51$

The Algorithm

- single-pass, polynomial time and space
- parameterless but accepts following:
  - minimum support threshold $\sigma \geq 2$ (default: 2)
  - min and max period (P_{min} and P_{max})
  - max jitter in period $J \geq 0$
- natural bound on max period if number of points in time is finite and known beforehand

Mining PSE Using a Pattern Tree

- crux of algorithm is pattern tree (record of what patterns are periodic and could become periodic)
- pattern tree is updated on-the-fly after each point in time
- anything no longer periodic is removed
- each node in tree contains subgraph and descriptor for each closed PSE
- descriptors are ordered pairs $D = \langle S = S_P(F), p\rangle$ where S is periodic support set of embedding of F and p the period

Pattern Tree

- pattern trees are subject to all descendants of node N representing proper subgraphs of F
- pattern tree is traversed for each new observation
- so, if given node does not have common subgraph with any other nodes, it will be removed

Subgraph Hash Map

- associates arbitrary subgraph with its node in tree
- utilized by update algorithm
- offers efficient constant look-up time since each node label is unique in each subgraph

Update Algorithm

- start with empty pattern tree at time t, read next graph G_t from input stream
- traverse pattern tree to update nodes with new info
- complete list of periodic subgraphs can be obtained from tree at any point
- breadth first traversal of tree

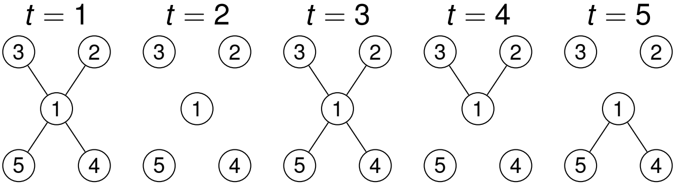
Details of the Algorithm

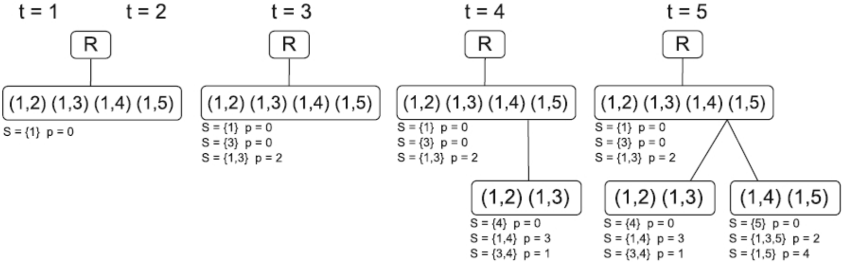
- update descriptors: if N is a subgraph of G_t, then N has appeared in its entirety at point t
- for all descriptors D, if next(D) $= t$, then t is added to support set
- if next(D) $< t$, descriptor is removed from tree

Details of the Algorithm

- propagate descriptors: let C be subgraph of both N and G_t
- subgraph C of N is present at point t, and if N has any descriptors D *s.t.* $\text{next}(D) = t$, then node for C receives copy of D
- if node for C already exists, then child is created
- dead subtree: if C is empty, then G_t and N have no common subgraph
- therefore, no child of N will have any common subgraph with G_t either
- then, subtree at N can be removed

Example: Pattern Tree





Datasets

Dataset	Vertices	Length	Avg. Density
Enron	82,614	2,588	0.028 ± 0.064
IMDB	15,011	13,967	0.22 ± 0.23

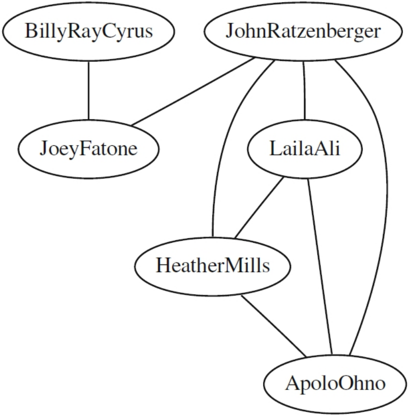
- Enron e-mails
- IMDB celebs: collect photographs of two or more people on site ((1 d sampling rate)).

Inherent Periodicity and Algorithm Tractability

- Enron and IMDB: attention is diverted to patterns with high average purity (patterns which are likely to exhibit truly periodic behavior)
- Enron: peak at 7 (weekly patterns)
- IMDB: peak at 364 (annual events)

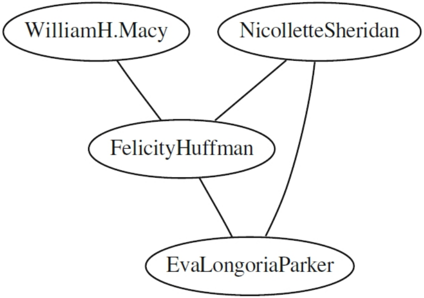
- algorithm manages space and execution time easily
- however, unable to mine subgraphs with $\sigma < 25$ for Enron

Examples of Interesting Periodic Subgraphs



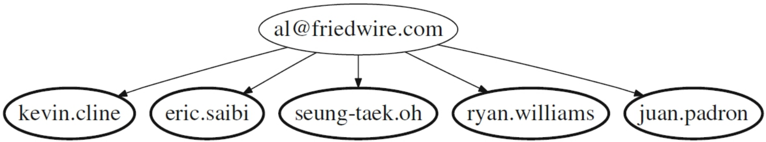
- complex pattern from IMDB photo database
- repeated approximately every week ($p = 7 \pm 2$)
- support is relatively low (3)
- non-trivial grouping of people
- all contestants on weekly reality TV show

Examples of Interesting Periodic Subgraphs



- IMDB database: approx. annually repeating pattern
- actresses in popular TV show, fourth vertex is spouse of one of actresses
- low average purity (0.4)
- non-trivial links indicate show's progression other than co-starring

Examples of Interesting Periodic Subgraphs



- highest periodic support in Enron dataset
- repeating every day for 84 consecutive days, including weekends
- $\exists$ large number of similar periodic patterns in Enron: one person emails group of people with periods from $1 - 14\,\mathrm{d}$
- weekly emails very popular
- can be used to infer functional communities

Summary

- formalized solution for tackling periodic subgraph problem
- One pass, efficient algorithm
- demonstrated effectiveness on two real-world social networks
- all periodic patterns are mined

Open Research

- probabilistic models of periodicity instead of strictly combinatorial ones
  - weighted edges instead of binary ones
  - change of edge weight must be greater than some threshold
  - application for brain networks
- interestingness of frequent patterns: usually application-dependent

Outline

Conclusions

- complex dynamic networks are ubiquitous
- usually, graphs are treated in static way
- networks typically change their structures in time
- focus: analysis of dynamic brain activity networks from EEG
- global approach: AR model for series of graph measurements
- local approach: periodic subgraph mining of dynamic networks

Difficulties and Controversies

data preprocessing:

- removal of biological artifacts (electromyographic (EMG), electrocardiograph (EKG))
- frequency bands (parallel graphs)

signal similarity: hundreds of methods possible...

same for graph similarity:

- edit distance
- maximum common subgraph distance
- kernel methods

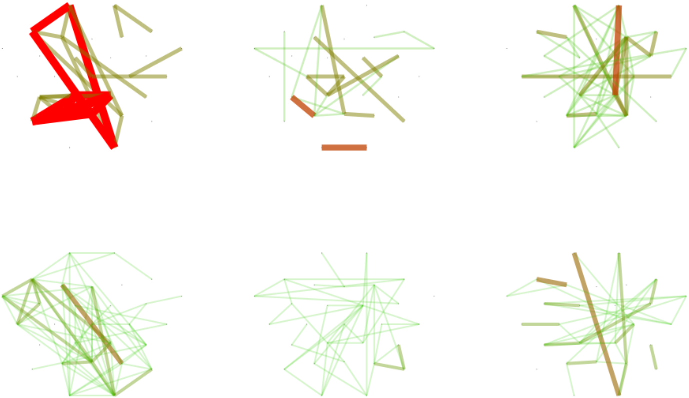
time series representations:

- symbolic approximations (Moewes and Kruse 2009)
- pattern mining (Moewes and Mörchen 2012)

Open Research Directions

- *robust* graph measures
- *weighted* subgraph mining
- *association rule learning* based on mined subgraphs
- *rule*-based systems for CDSS
- *other* social networks, *e.g.* Facebook, Twitter, functional Magnetic Resonance Imaging (fMRI)

Thank you very much for your indulgence :-)



Literature I

Erdős Paul and Rényi Alfréd (1960). "On the Evolution of Random Graphs." *Publications of the Mathematical Institute of the Hungarian Academy of Sciences* **5**:17–61.

Harary F. and Gupta G. (1997). "Dynamic graph models." *Mathematical and Computer Modelling* **25**(7):79–87.

Watts Duncan J. and Strogatz Steven H. (1998). "Collective dynamics of 'small-world' networks." *Nature* **393**(6684):440–442.

Barabási Albert-László and Albert Réka (1999). "Emergence of Scaling in Random Networks." *Science* **286**(5439):509 –512.

Stephan K E et al. (2000). "Computational analysis of functional connectivity between areas of primate cerebral cortex." *Philosophical Transactions of the Royal Society B: Biological Sciences* **355**(1393).111–126.

Latora Vito and Marchiori Massimo (2001). "Efficient Behavior of Small-World Networks." *Physical Review Letters* **87**(19):198701.

Literature II

Stam C. J. and Dijk B. W. van (2002). "Synchronization likelihood: an unbiased measure of generalized synchronization in multivariate data sets." *Physica D: Nonlinear Phenomena* **163**(3-4):236–251.

Desikan Prasanna and Srivastava Jaideep (2004). "Mining Temporally Evolving Graphs." In: *Proceedings of the Sixth International Workshop on Knowledge Discovery from the Web (WEBKDD 2004)*. Ed. by Bamshad Mobasher et al. ACM Press, Seattle, Washington, USA:13–22.

Pincombe Brandom (2005). "Anomaly Detection in Time Series of Graphs using ARMA Processes." *ASOR Bulletin* **24**(4).

Montez T. et al. (2006). "Synchronization likelihood with explicit time-frequency priors." *NeuroImage* **33**(4): 1117–1125.

Sporns Olaf (2007). "Brain connectivity." *Scholarpedia Journal* **2**(10):4695.

Box George E. P., Jenkins Gwilym M., Reinsel Gregory C. (2008). *Time Series Analysis: Forecasting and Control*. ed. 4th. Wiley.

Bullmore Ed, Barnes Anna, et al. (2009). "Generic aspects of complexity in brain imaging data and other biological systems." *NeuroImage* **47**(3):1125–1134.

Literature III

Bullmore Ed and Sporns Olaf (2009). "Complex brain networks: graph theoretical analysis of structural and functional systems." *Nature Reviews Neuroscience* **10**(3):186–198.

Moewes Christian and Kruse Rudolf (2009). "Zuordnen von linguistischen Ausdrücken zu Motiven in Zeitreihen." *at-Automatisierungstechnik* **57**(3):146–154.

Lahiri Mayank and Berger-Wolf Tanya Y. (2010). "Periodic subgraph mining in dynamic networks." *Knowledge and Information Systems* **24**:467–497.

Sporns Olaf (2010). *Networks of the Brain*. MIT Press, Cambridge, MA, USA.

Steen Maarten van (2010). *Graph Theory and Complex Networks: An Introduction*. createspace.

Held Pascal et al. (2012). "Advanced analysis of dynamic graphs in social and neural networks." In: *Towards Advanced Data Analysis by Combining Soft Computing and Statistics*. Studies in Fuzziness and Soft Computing. Springer-Verlag, Berlin / Heidelberg, Germany.

Moewes Christian and Kruse Rudolf (2012). "Patterns and Models for the Analysis of Real-world Time Series." In: *ECAI 2012, Montpellier, France*.

Literature IV

Moewes Christian, Kruse Rudolf, et al. (2012). "Analysis of Dynamic Brain Networks using ARMA Models." In: *IJCNN 2012, Brisbane, Australia*.

Moewes Christian and Mörchen Fabian (2012). "Time Series Mining." *WIREs Data Mining and Knowledge Discovery*.