Conditional Fuzzy C Means

A fuzzy clustering approach for mining event-related dynamics

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Contents

- The problem
- Our approach
- Fuzzy Clustering
- Conditional Fuzzy Clustering
- Graph-Theoretic Visualization techniques
- The experiments and the datasets
- Applications
- Future Work
- Conclusions

The problem

Visualizing the variability of MEG responses

understanding the single-trial variability

Describe the single-trial (EEG) variability in the presence of artifacts

make single-trial analysis robust, robust prototyping

Our approach

criteria ⟵ ***CONDITIONAL*** ⟶ grades

content constraints

~~0 or 1~~ ⟵ ***FUZZY*** ⟶ [0, 1]

partial membership

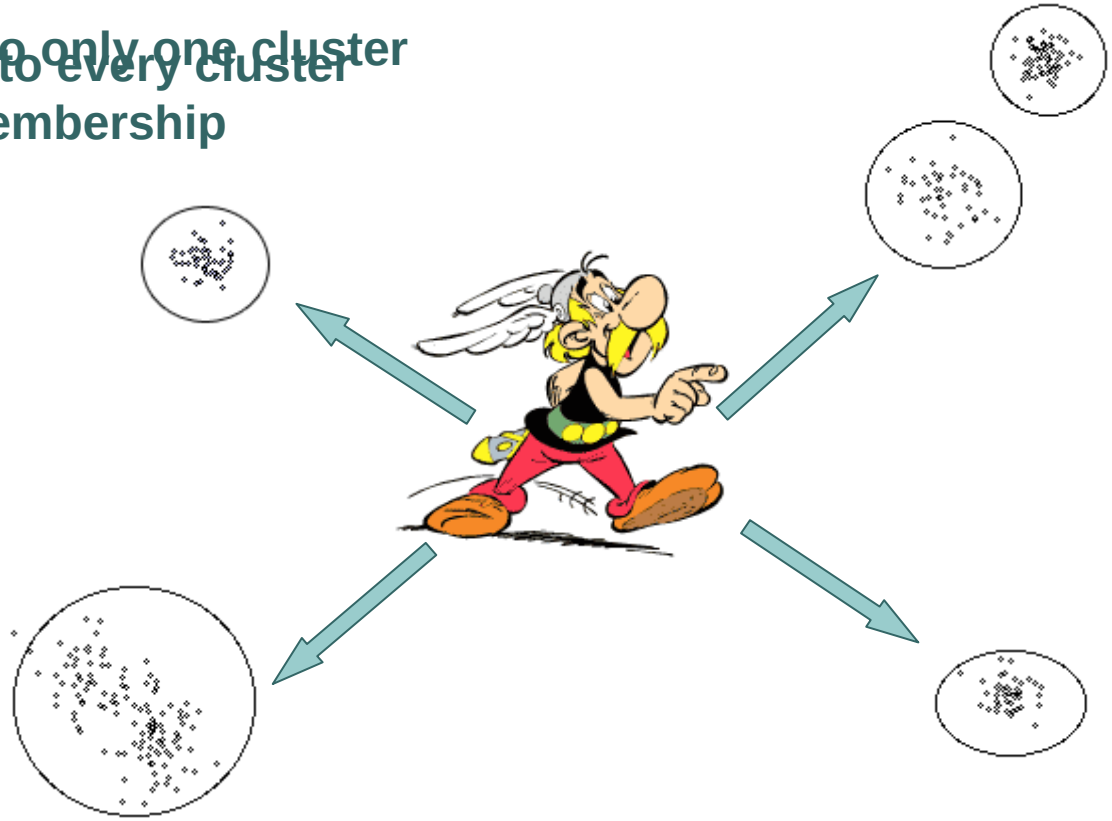
 ⟵ ***CLUSTERING*** ⟶ 

creating clusters

Fuzzy Clustering

Every Pattern to only one cluster

Every Pattern to every cluster with partial membership



Fuzzy C Means

Xdata$_{Nxp}$

U membership matrix

$$\begin{bmatrix} u_{11} & \cdots & u_{1N} \\ \vdots & \ddots & \vdots \\ u_{C1} & \cdots & u_{CN} \end{bmatrix}$$

$$V_i = \frac{\sum_{k=1}^{N} u_{ij}^{\ m} x_k}{\sum_{k=1}^{N} u_{ij}^{\ m}}$$

Objective function

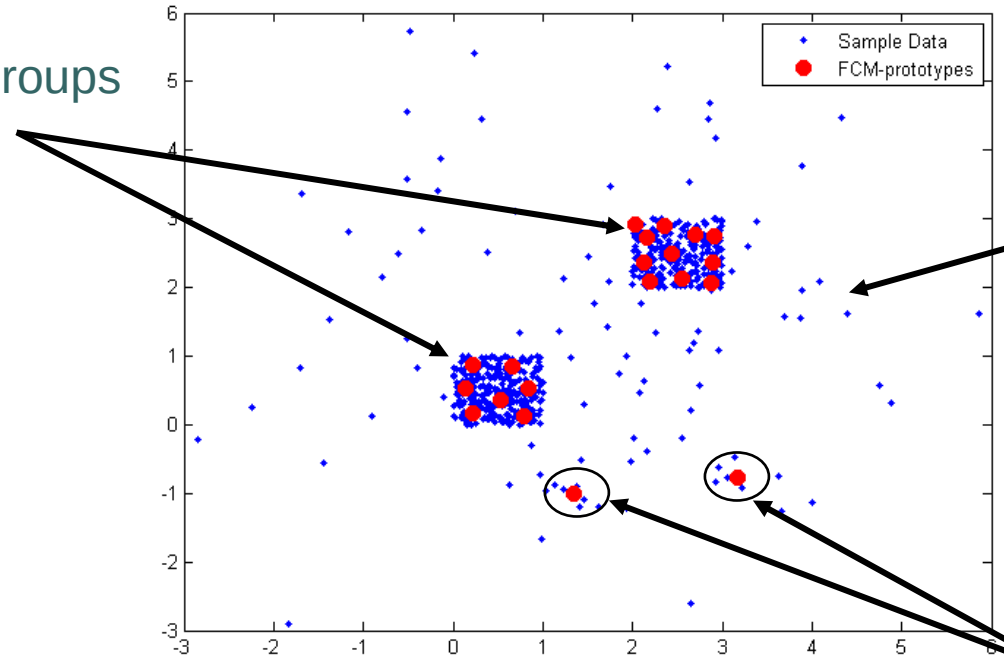
$$|Q(t) - Q(t-1)| < \varepsilon$$

CONTINUE | STOP

Iterative procedure

FCM 2D Example

compact groups

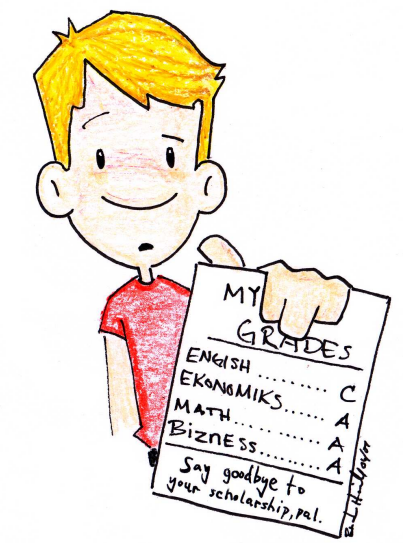


spurious patterns

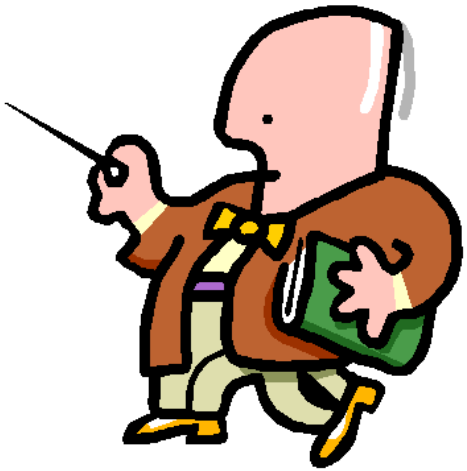
FCM sensitivity
to noisy data

Conditional Fuzzy Clustering

The presence of Condition(s)



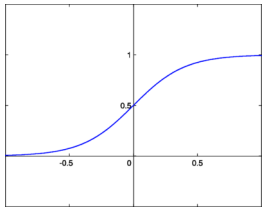
mark



Pattern

Condition(s)

Conditional Fuzzy C Means



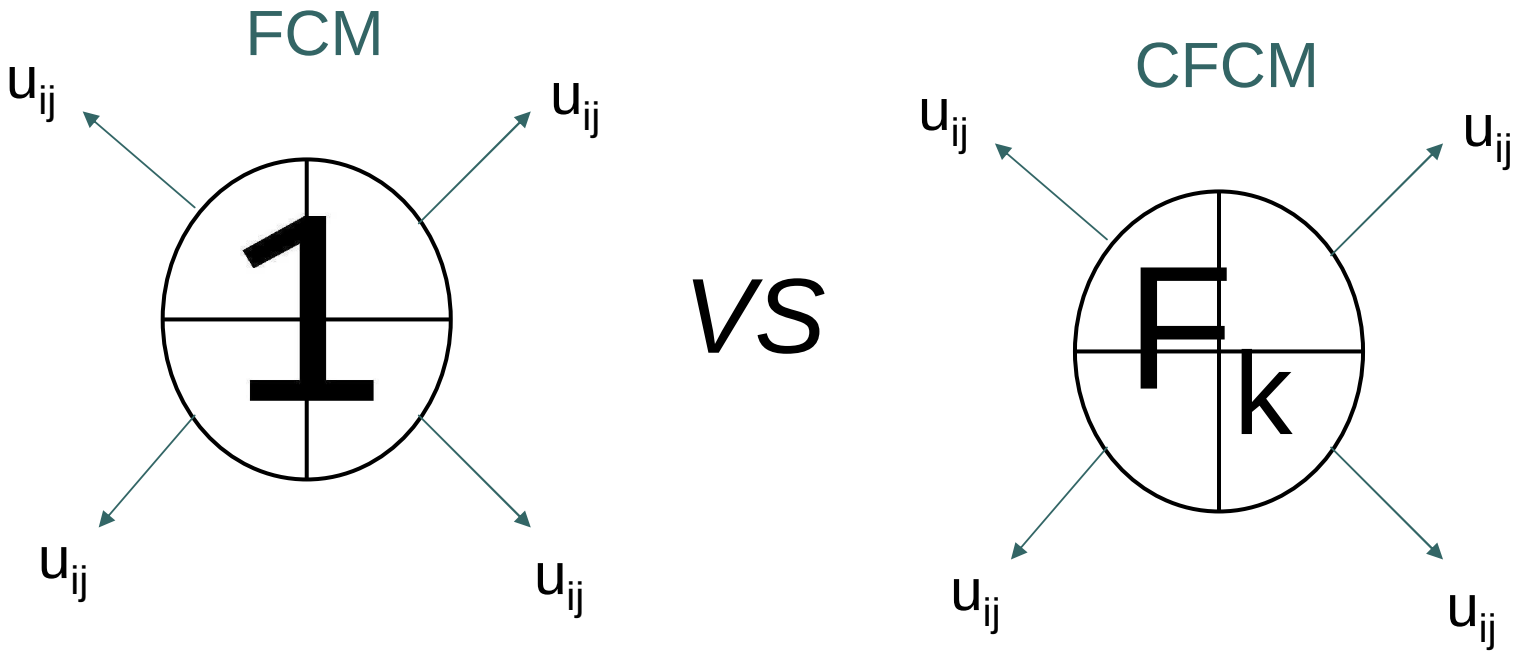
$$F = [\, f_1, f_2, \ldots, f_N \,]$$

scaled to [0, 1]

<Xdata, F> → CFCM → <U, Centroids>

F affects the computations of U matrix and consequently the centroids.

FCM VS CFCM



Graph-theoretic Visualization Techniques

Topology Representing Graphs

Build a graph **G** [C x C] ⟹ Topological relations between prototypes

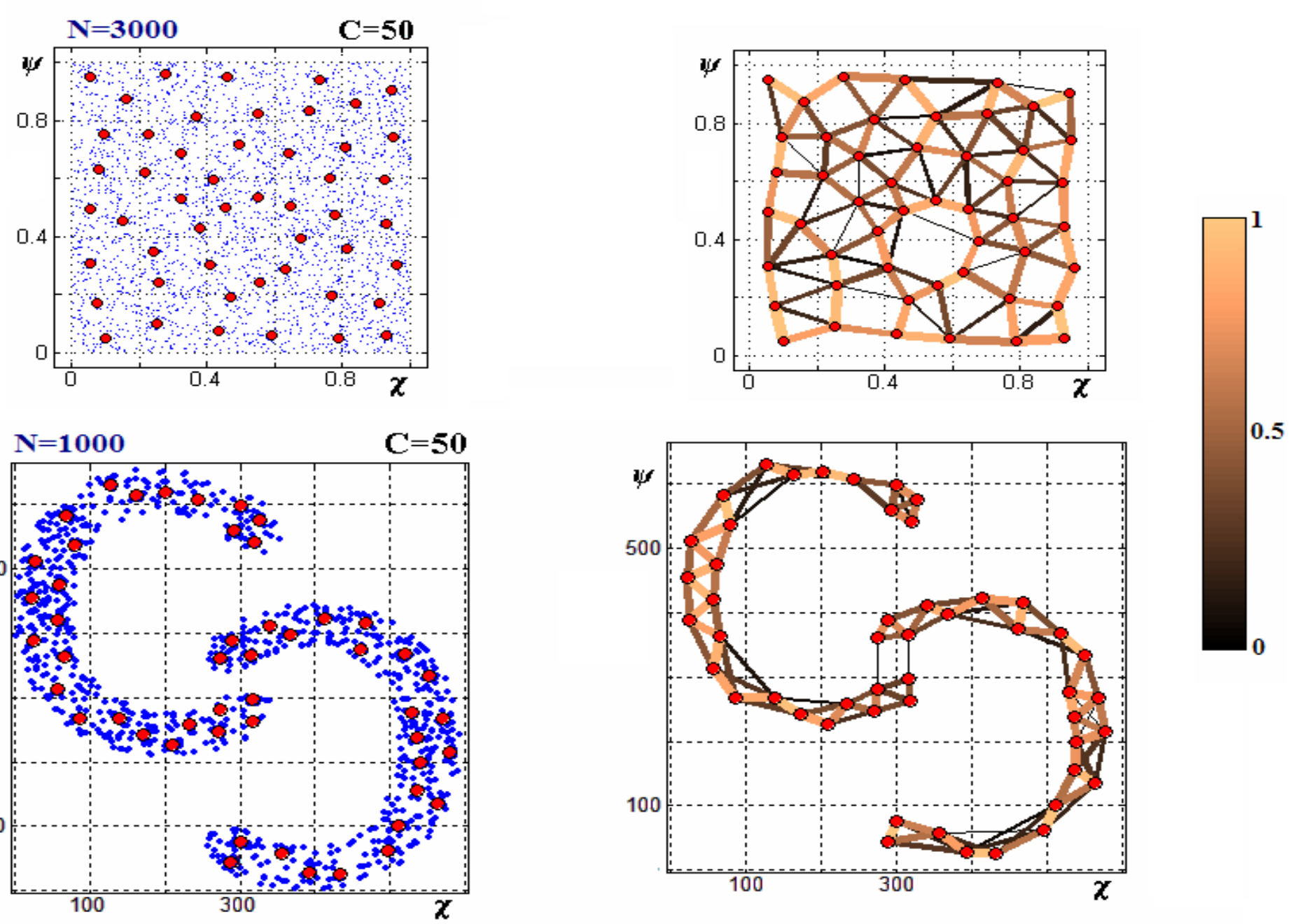
$\mathbf{G_{ij}}$ corresponding to the strength of connection between prototypes O_i and O_j

Computation of the graph **G**

- For each pattern find the nearest prototypes and increase the corresponding values in G matrix

- Simple elementwise thresholding → Adjacency Matrix **A**

A: a link connects two nearby prototypes only when they are natural neighbors over the manifold


N=3000
C=50
ψ
0.8
0.4
0
0
0.4
0.8
χ
N=1000
C=50
ψ
500
100
100
300
χ
1
0.5
0

Graph-theoretic Visualization Techniques

Compute the G graph via CFCM results

Apply CFCM algorithm: (O, U) = CFCM(X, F_k, C)

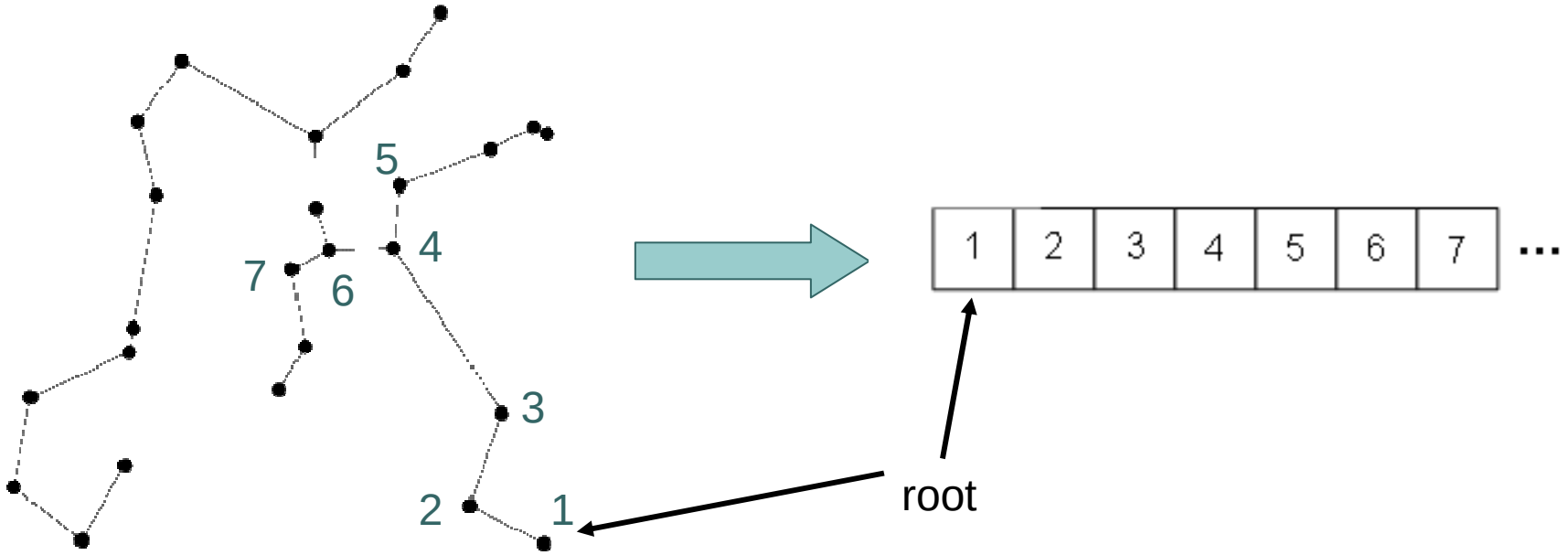
Build $U^{'} = [u_{ij}^{'}]_{CxN}, such\,that\; u_{ij}^{'} = u_{ij}.\theta(u_{ij} - \tau)$

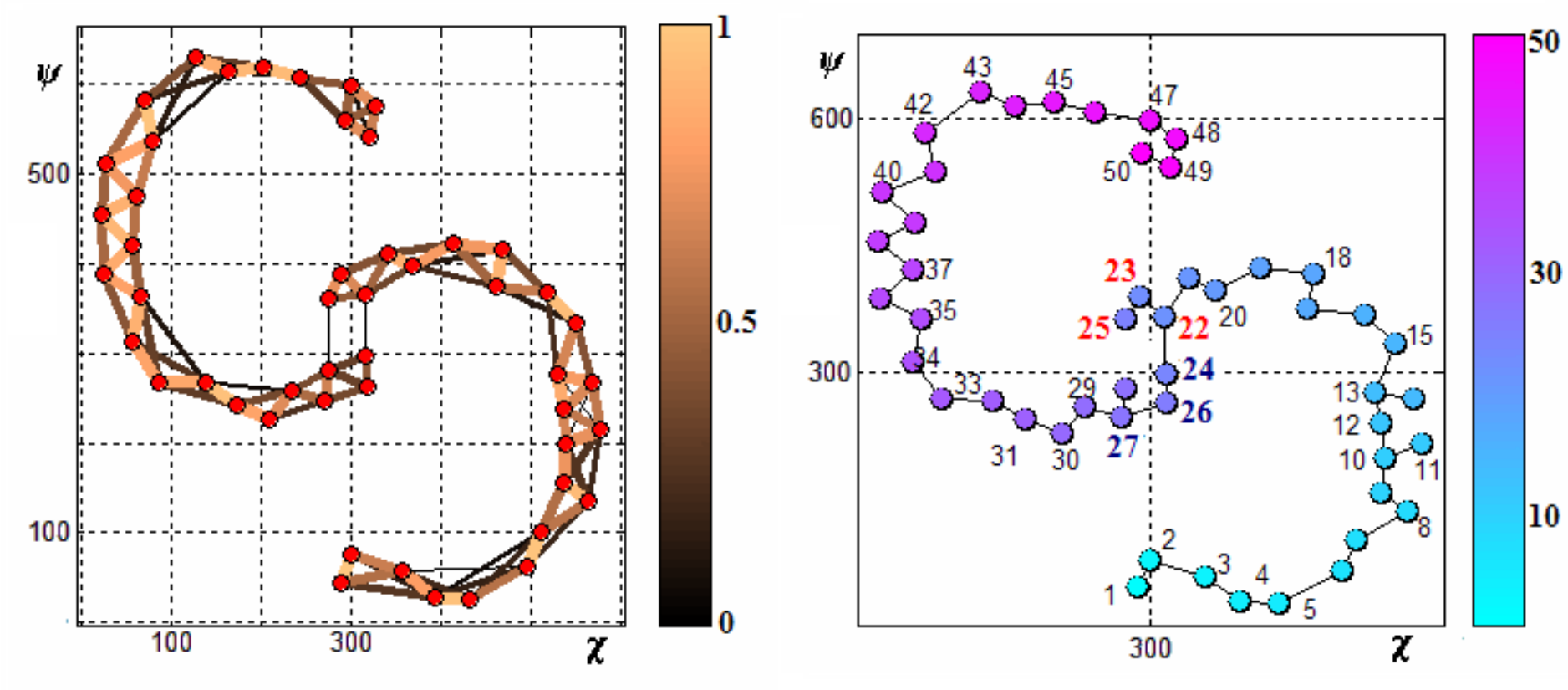
Compute G = U'.U'^{T} ⟹ FCG: Fuzzy Connectivity Graph

Graph-theoretic Visualization Techniques

Minimal Spanning Tree

MST-ordering





Minimal Spanning Tree with MST-ordering

Graph-theoretic Visualization Techniques

Locality Preserving Projections

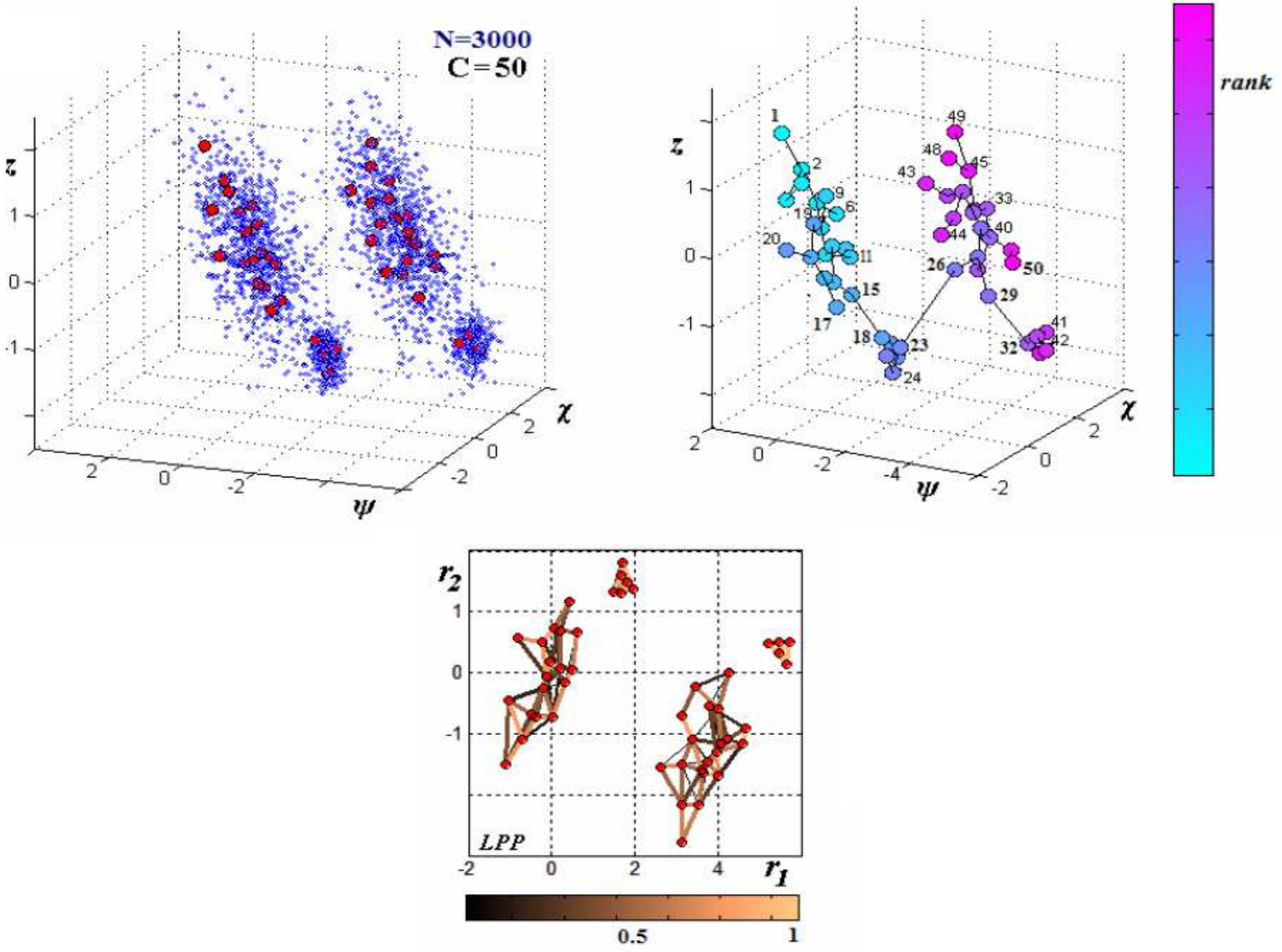
Dimensionality Reduction technique $R^p \rightarrow R^r$ $r<p$

Linear approach ≠ MDS, LE, ISOMAP

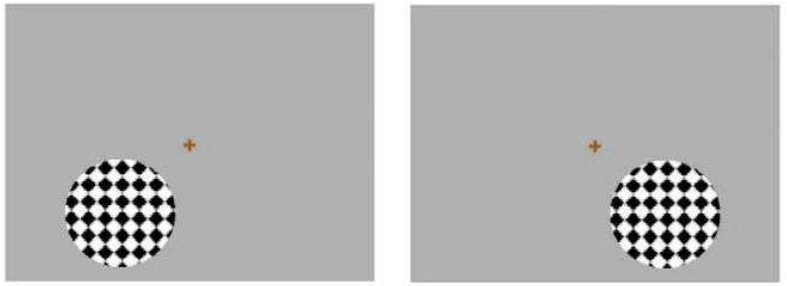
- generalized eigenvector problem
- use of FCG matrix
- select the first r eigenvectors and tabulate them (A_{pxr} matrix)

$$P = [p_{ij}]_{Cxr} = OA$$

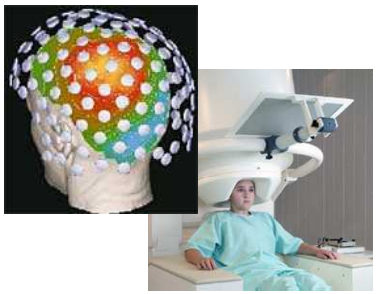
Alternative to PCA: different criteria, direct entrance of a new point into the subspace


N=3000
C=50
z
χ
ψ
rank
LPP
r_2
r_1
0.5
1

The experiments



Magnetoencephalography



+ 197 single trials

+ control recording

Electroencephalography

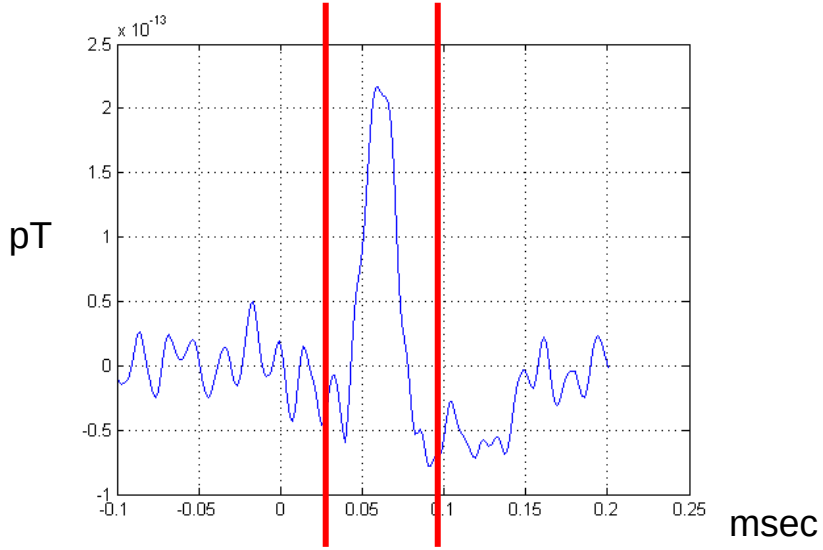
110 single trials

Online outlier rejection

The datasets

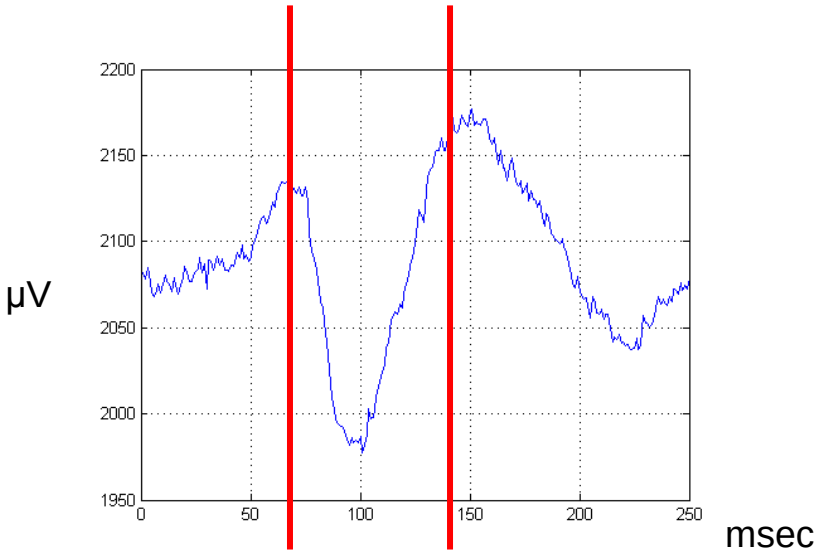
Feature Extraction

MEG



X_data [197 x p_1], p:number of features

EEG

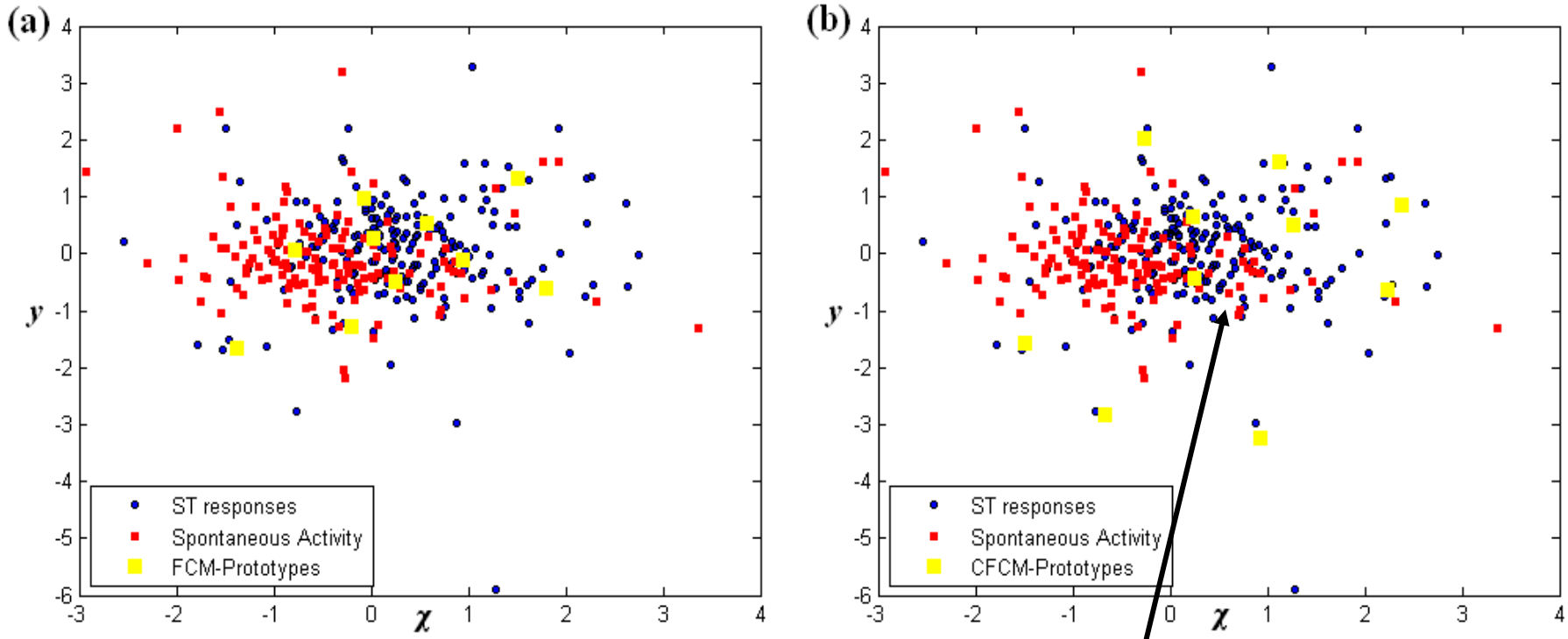


X_data [110 x p_2], p:number of features

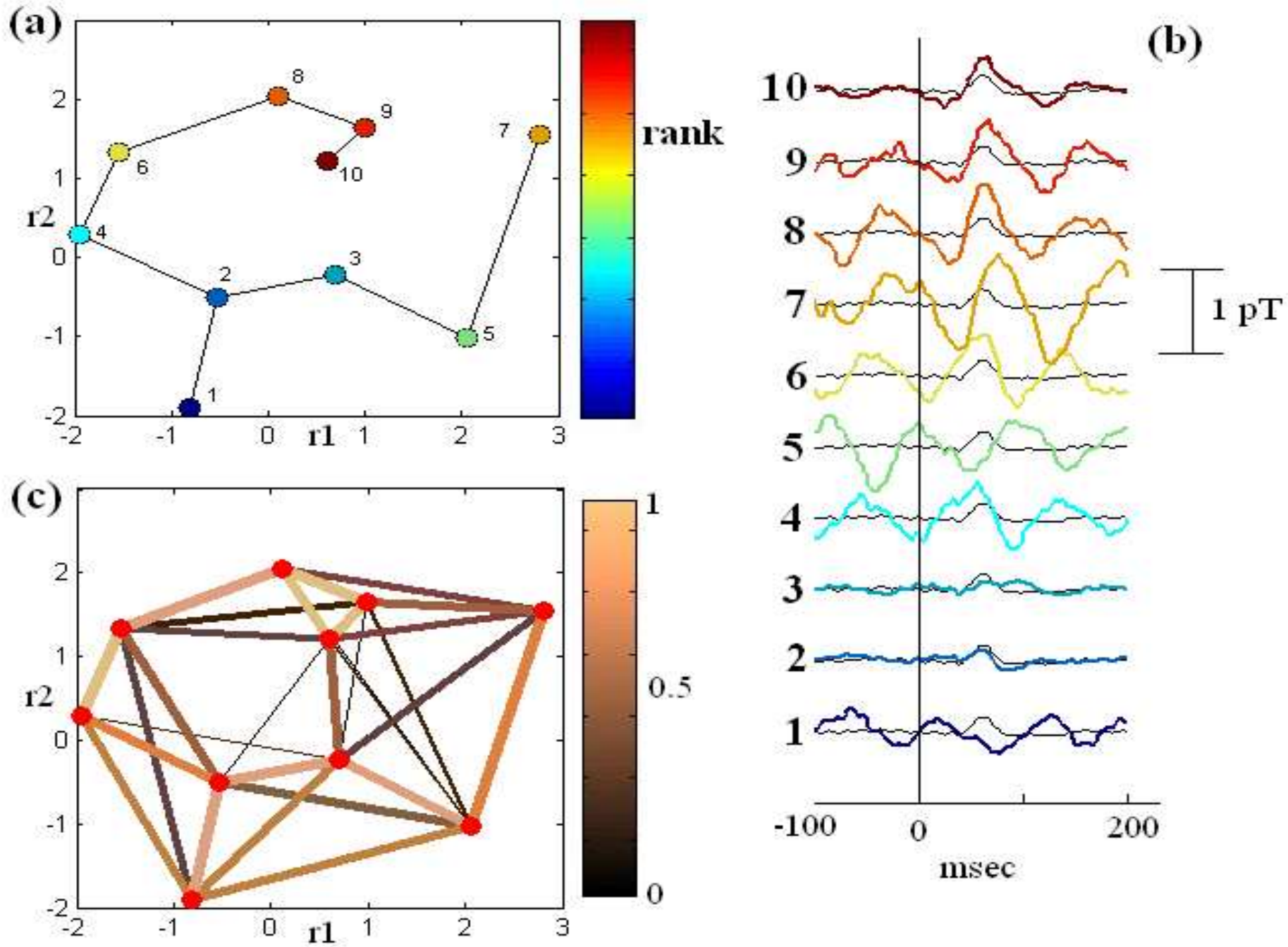
Applications (MEG)

Exploit the background noise for better clustering

MEG single trials + Spontaneous activity as a auxiliary set of signals



Exploit the distances to extract the grades


(a)
r2
r1
rank
(b)
10
9
8
7
6
5
4
3
2
1
1 pT
-100
0
200
msec
(c)
r2
r1
1
0.5
0

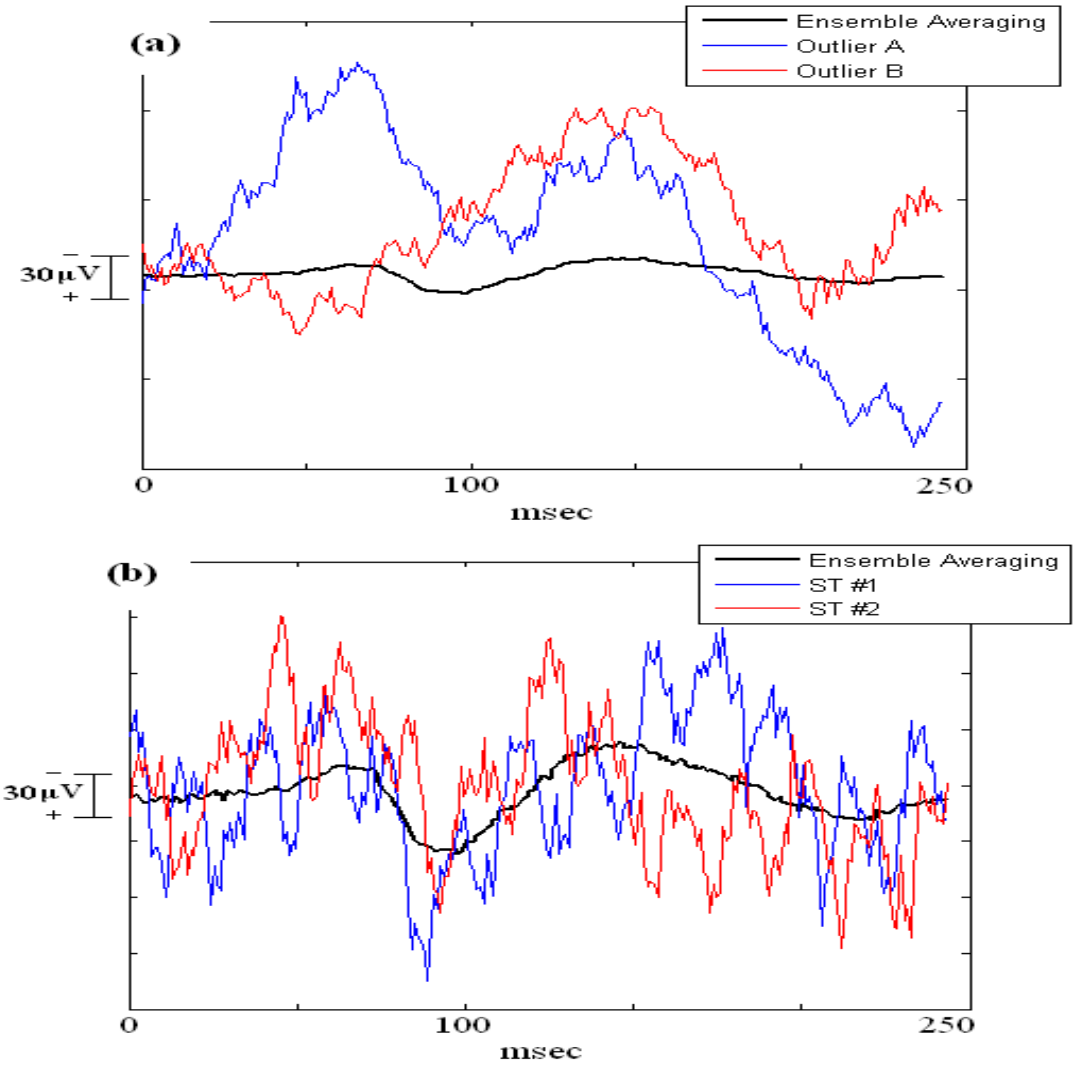
Applications (EEG)

Robust Prototyping

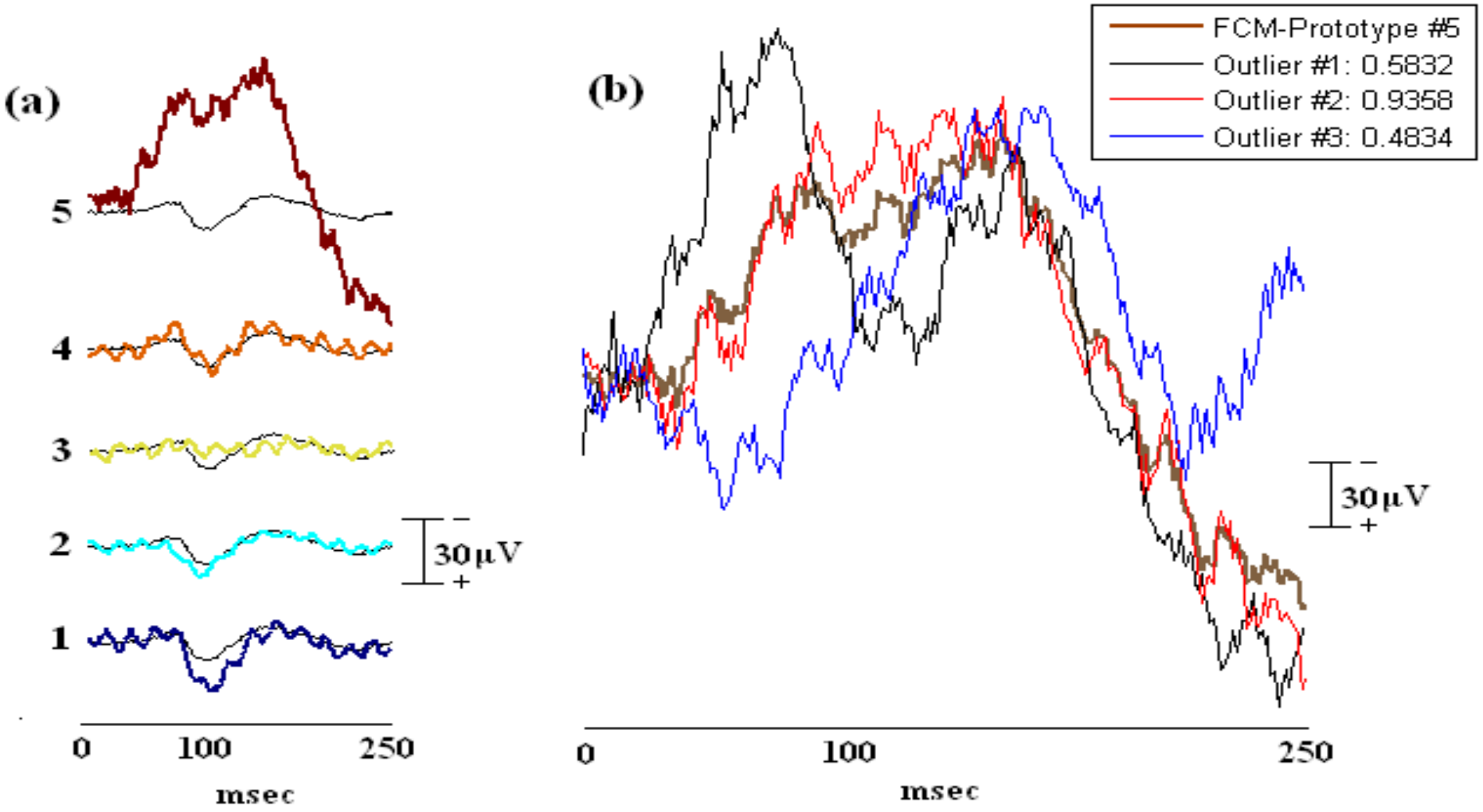
Elongate the possible outliers

from the clustering procedure

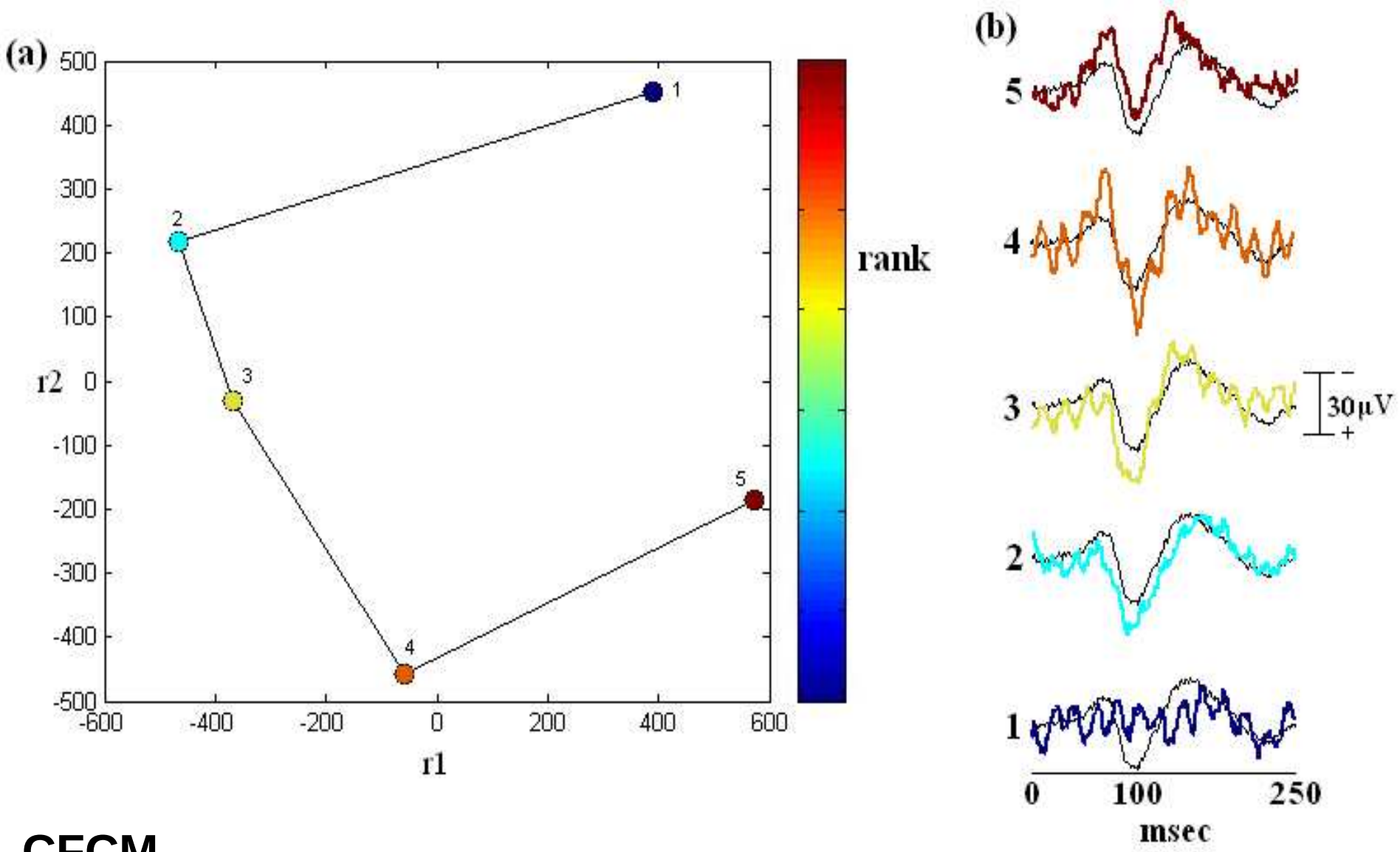
Find the distances from the nearest neighbors and compute the grades for every pattern



A


(a)
5
4
3
2
1
30μV
0
100
250
msec
(b)
FCM-Prototype #5
Outlier #1: 0.5832
Outlier #2: 0.9358
Outlier #3: 0.4834
30μV
0
100
250
msec

FCM


(a)
500
400
300
200
100
r2 0
-100
-200
-300
-400
-500
-600
-400
-200
0
200
400
600
r1
1
2
3
4
5
rank
(b)
5
4
3
2
1
30μV
0
100
250
msec

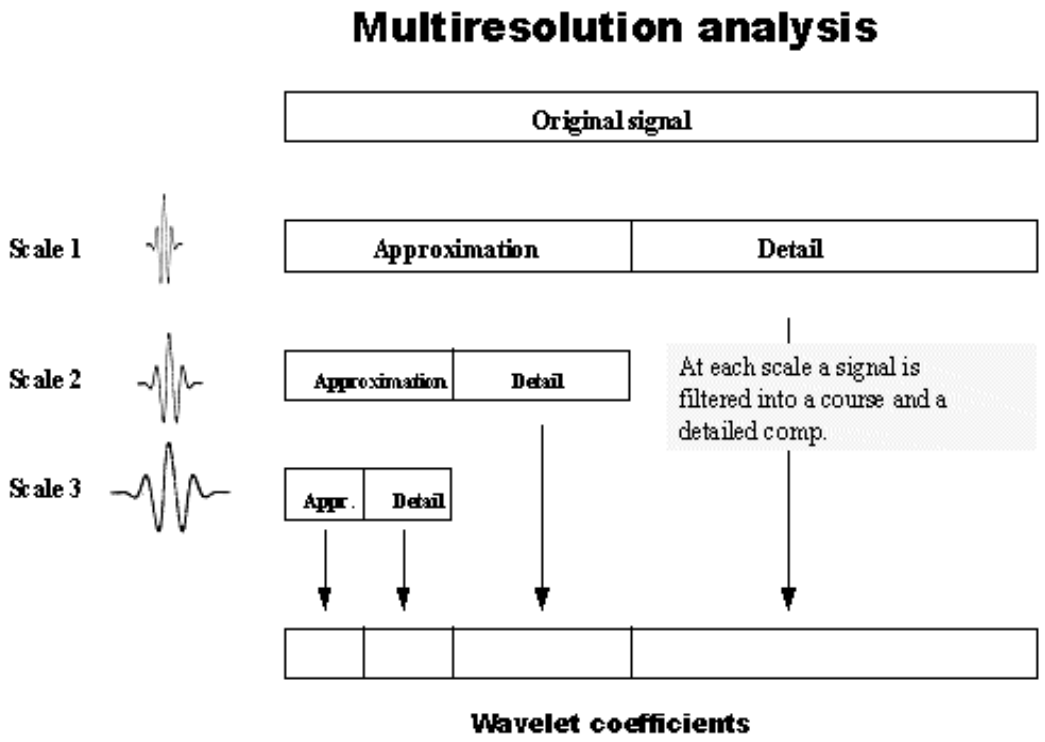
CFCM

Future Work

Knowledge-Based Clustering Algorithms

- *conditional fuzzy clustering wavelet transform*

- *horizontal collaborative clustering wavelet transform*



Conclusions

Through the proposed methodology

- exploit the presence of noisy data
- elongate the outliers from the clustering procedure

Graph-Theoretic Visualization Techniques

- study the variability of brain signals
- study the relationships between clustering results

Paper submitted

"*Using Conditional FCM to mine event-related dynamics*"