Independent Component Analysis

Applications in EEG and MEG

Artifacts removing

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EEG & MEG

- **EEG:** measures potential distribution on scalp by placing electrodes

- **MEG:** measuers magnetic fields associate with current (more sophisticated)

EEG & MEG

- **EEG:** Used for measuring spontaneous activity and for study of evoked potentials (triggerd by a stimulus, e.g. Auditory or somatosensory)
- **MEG:** Use for cognitive brain research

Application of EEG & MEG

- Artifacts (signals not generated by brain activity, but some external disturbers (muscles,...))
- 122 - sensor scalp magnetometer.
- Test-person should blink眨眼, make horizontal saccades扫视, bite 咬 for 20s
- Other artifact: digital watch 1m away from magnetometer.

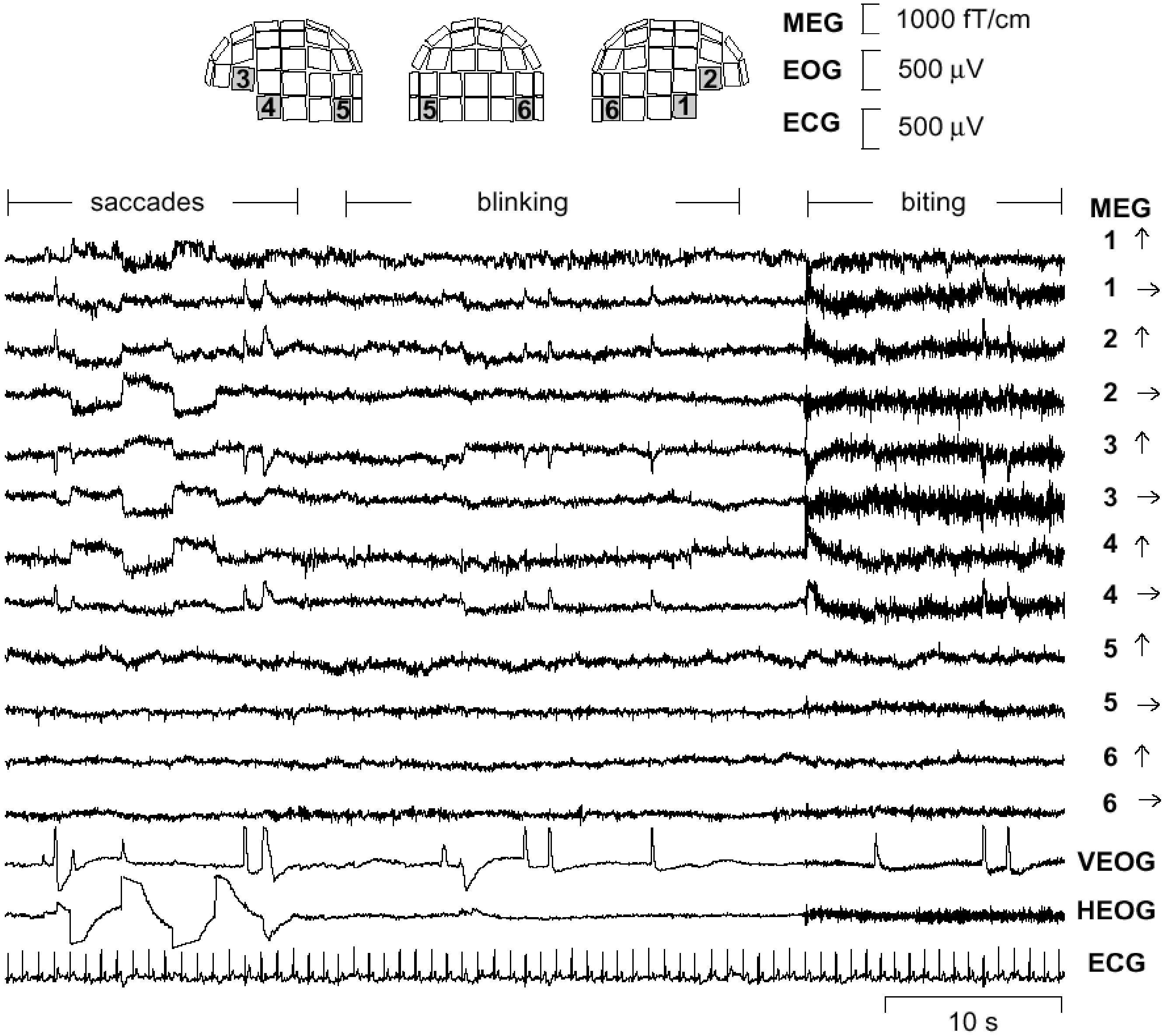
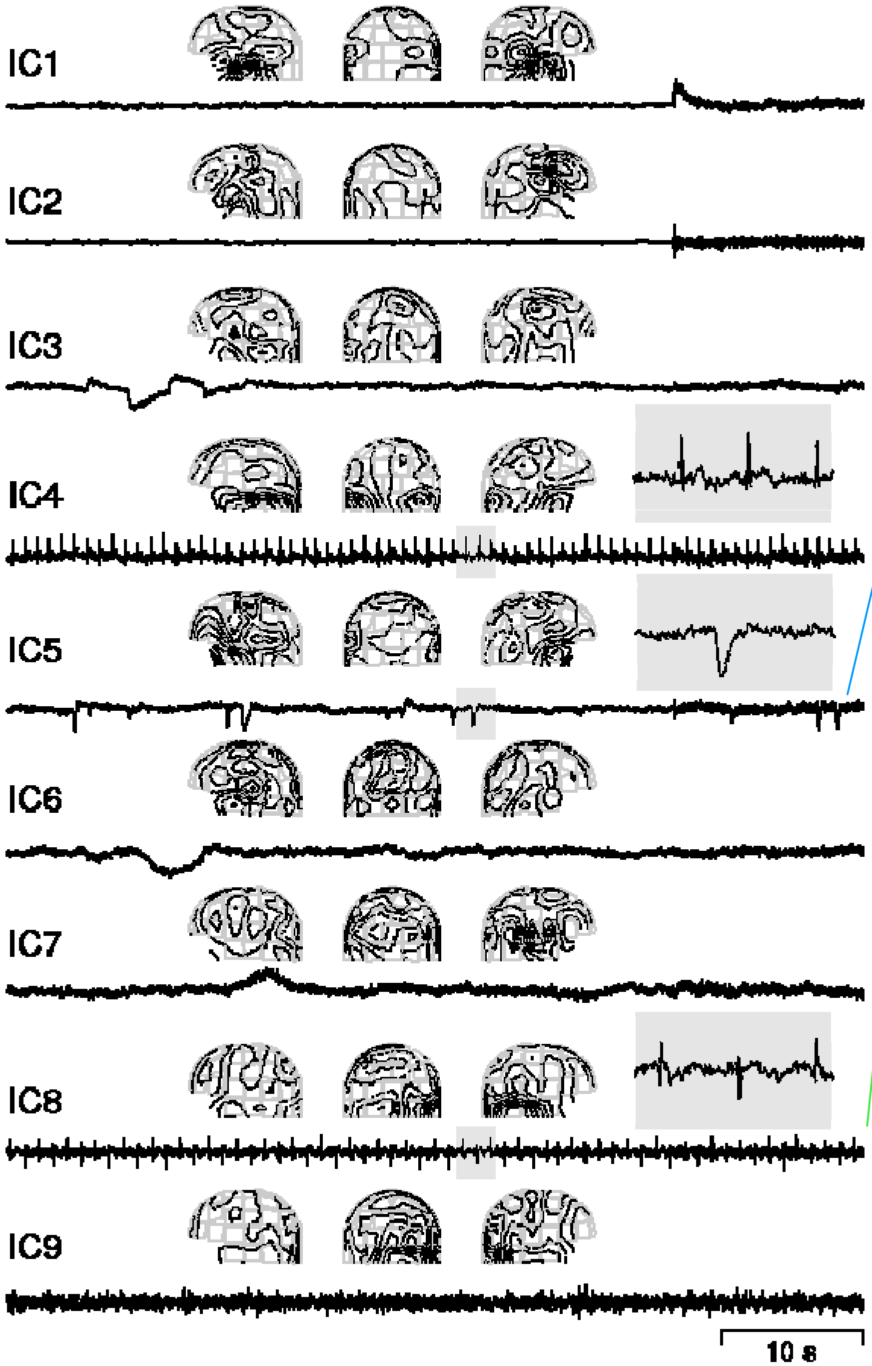


Figure 1: *Samples of MEG signals, showing artifacts produced by blinking, saccades, biting and cardiac cycle.*



Activation of 2 diff. Muscles sets

Horizontal eye movement

Heart beating, digital watch

Breathing, bumps caused by overlearning

Faulty sensor

ICA on other measure techniques

Functional Magnetic resonance images

1. Huafu Chen, Dezhong Yao, Yan Zhuo, and Lin Chen. Analysis of fMRI Data by Blind Separation of Data in a Tiny Spatial Domain into Independent Temporal Component.. Brain Topography, Volume 15, Number 4, 2003

Removing artifacts from cardiographic (heart) signals

1. Barbati G, Porcaro C, Zappasodi F, Rossini PM, Tecchio F. Optimization of an independent component analysis approach for artifact identification and removal in magnetoencephalographic signals.Clin Neurophysiol. 2004 May;115(5):1220-32.

Independent Component Analysis

PART IV

Applications in Financial Application

Finding hidden factors in financial data

Neural Networks

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ICA reveals hidden factors

Exp: Try to find the fundamental factors common to all stores affecting cashflow (cashflow of some stores of same retail零售 chain)

ICA-Model:

$$x_i(t) = \sum_j a_{ij} s_j(t)$$

$x_i(t)$... financial time series

ICs in time series

- Seasonal variation due to holidays
- Other factors having effect on purchasing power of customers (e.g. Price-changes of commodities)

* Depending on advertisement, effect of this factors on cashflow are diff.

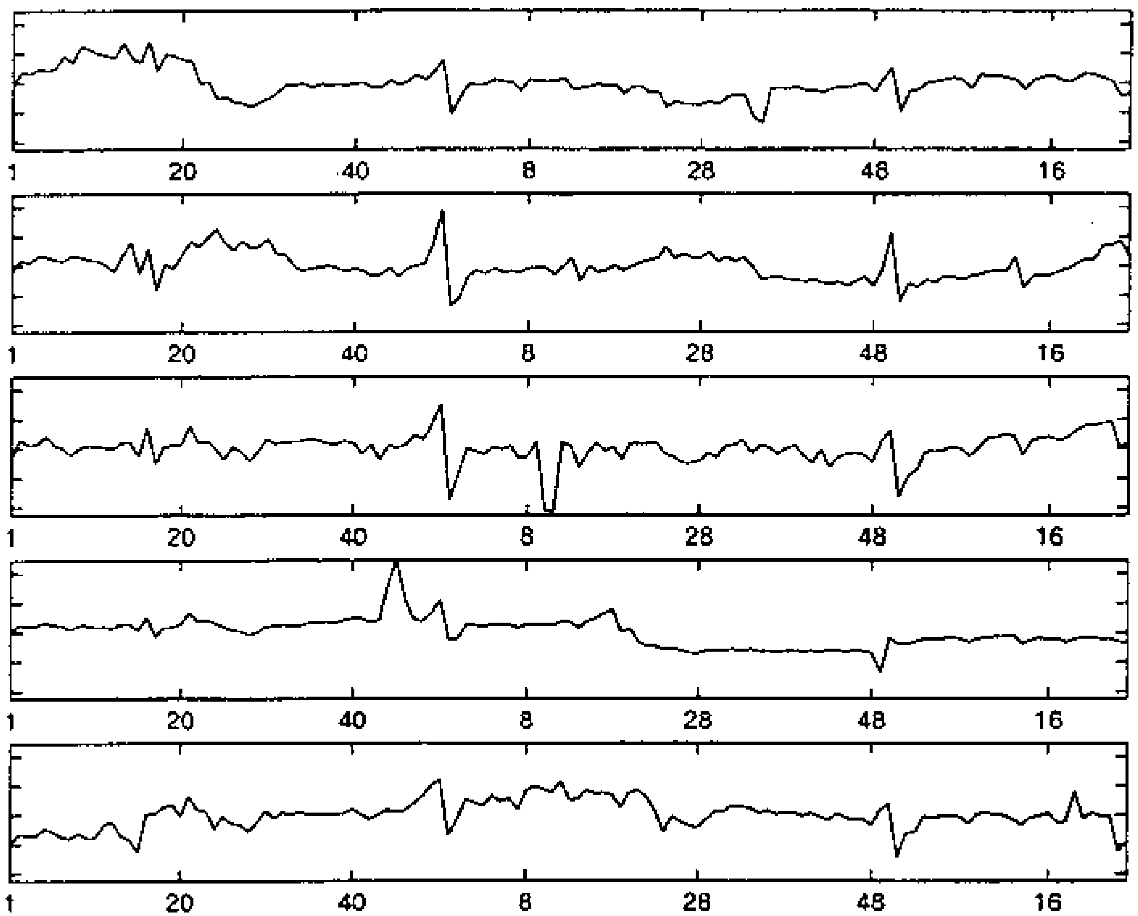
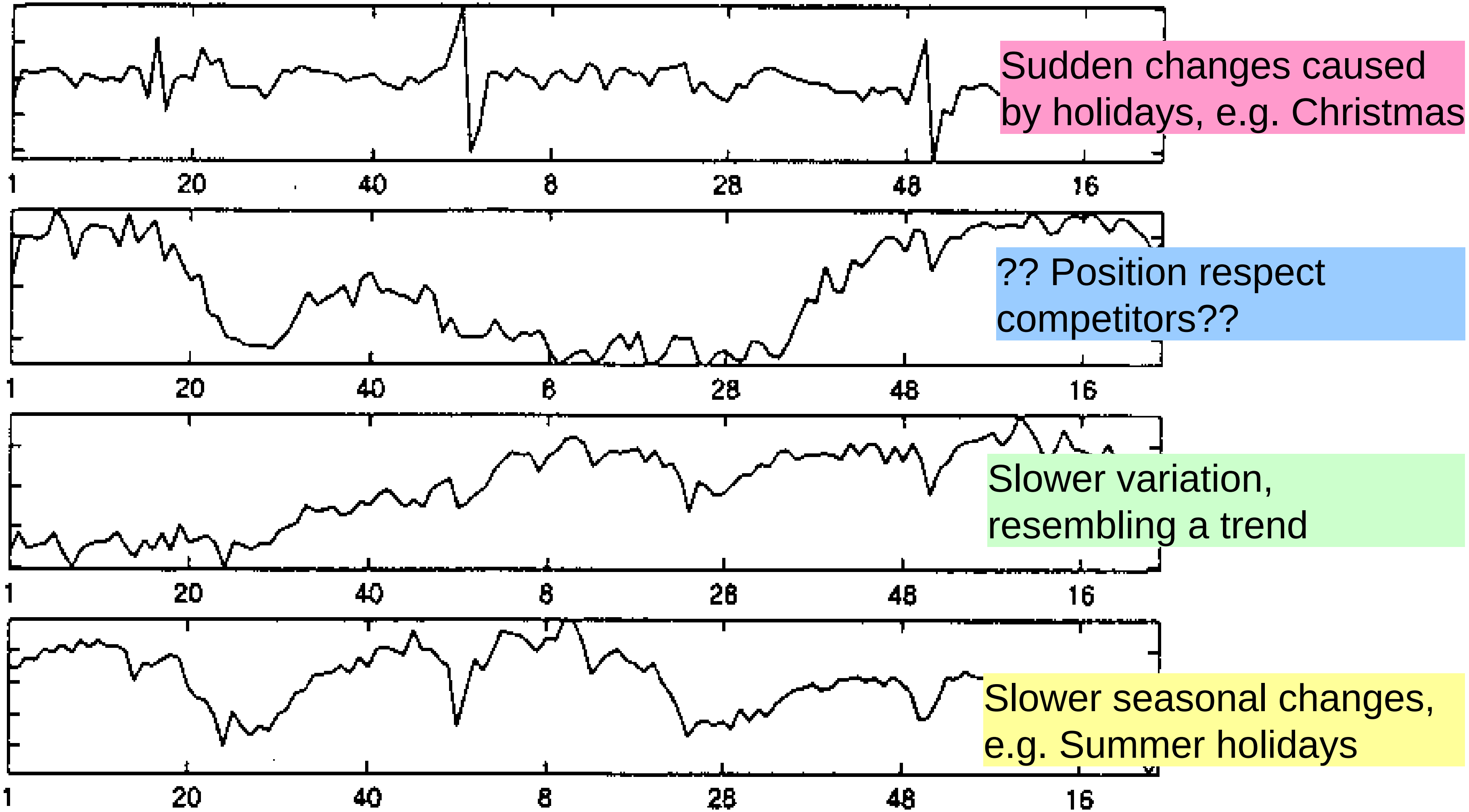


Fig. 24.1 Five samples of the 40 original cashflow time series (mean removed, normalized to unit standard deviation). Horizontal axis: time in weeks over 140 weeks. (Adapted from [245].)

Using ICA...

- Data first prewhitened using PCA
- **Problem**: no knowledge about number of independent components.

  (approx.: using eigenvalue spectrum of data covariance matrix)
- **Here**: FastICA with 4 ind. Components


Sudden changes caused by holidays, e.g. Christmas
?? Position respect competitors??
Slower variation, resembling a trend
Slower seasonal changes, e.g. Summer holidays
1
20
40
8
28
48
16

Demos

- Demos-Download-Site:
  http://sig.enst.fr/~cardoso/icacentral/algos.html
- Online-Demo:

  http://www.lis.inpg.fr/demos/sep_sourc/ICAdemo

– Homepage von Aapo Hyvärinen

  http://www.cis.hut.fi/~aapo/

Literature-References

- **Independent Component Analysis:** Aapo Hyvärinen, Juha Karhunen, Erkki Oja; John Wiley & Sons, Inc.
- **Vicardo Nuno Vigário, Dr. Tech**

  http://www.cis.hut.fi/~rvigario
- **Applying independent component analysis** (ICA) and time/frequency analysis to collections of single-trial EEG (or MEG) data, or to collections of averaged event-related potential (ERP) or field (ERF) epochs.

  http://www.cnl.salk.edu/~scott/PNAS.html
- **ICA-CNL Overview:**

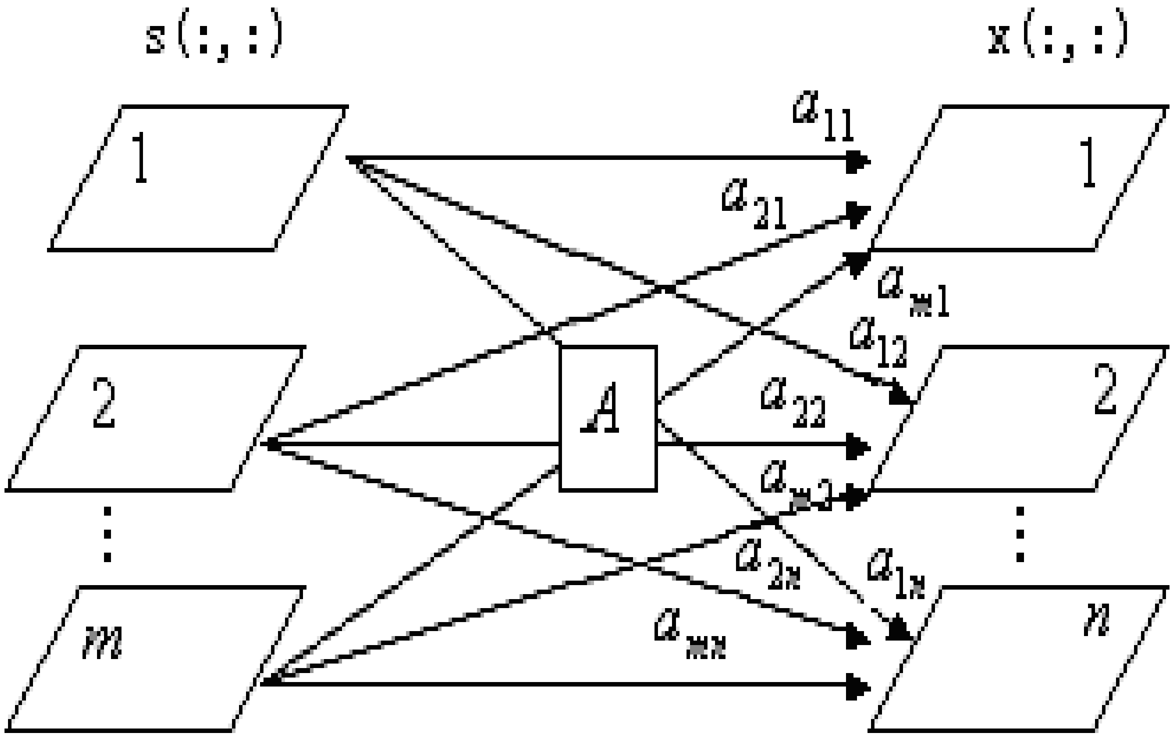
Literature-References

- ICA and Clinical EEG, ICA and functional MRI
  http://www.cnl.salk.edu/~martin/index.html

ICA study
at NeuroInformatic Center of UESTC

1.ICA模型

设无噪声信号模型为　　　**X=As**



A 为信号混合矩阵， x是 N维观测信号向量， s 是 M (N>M) 维原始信号向量。

由（1）可见，信号S放大 k 倍与A的相应列缩小k倍的结果相同,从而决定了ICA得到的信号存在强度的不确定性。为此，在求解时往往把观测信号先转化为有单位协方差的信号，即在ICA之前先有一个白化过程[2]。

设信号向量y的联合概率密度为p(y)，而每一个信号成分的概率密度为$p(y_i)$，则信号向量的互信息可以表示为：

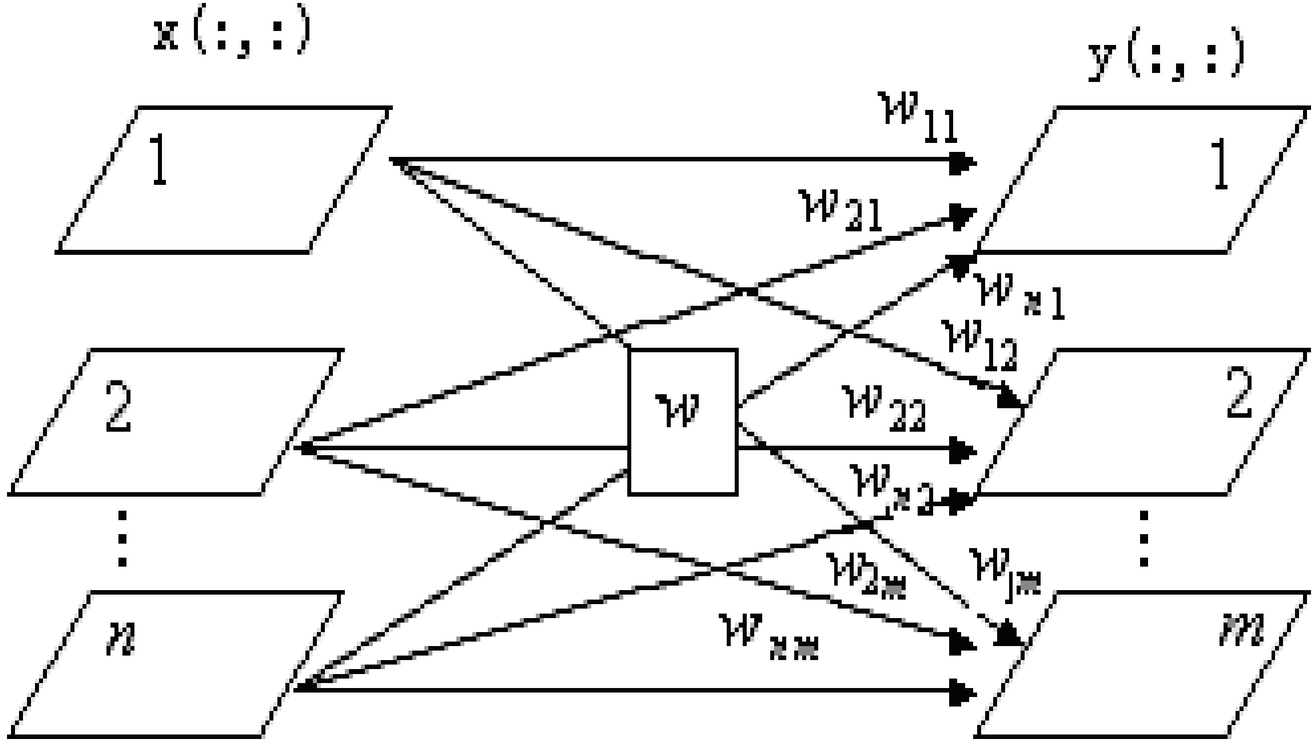
$$I(y) = \int p(y) \log \frac{p(y)}{\prod_{i=1}^{M} p_i(y_i)} dy \qquad (2)$$

当各个信号成份相互独立时， $p(y)=\prod_{i=1}^{M} p(y_i)$

则 $I(y)=0$ 。 (3)

ICA的目的是：在我们不知道混合矩阵的情况下，寻找线性映射w，从观测信号中提取不能被直接观测的原信号， 这里把它记为:

$$y=wx=wAs \qquad (4)$$



2. ICA理论：

(1) 互信息极小判据

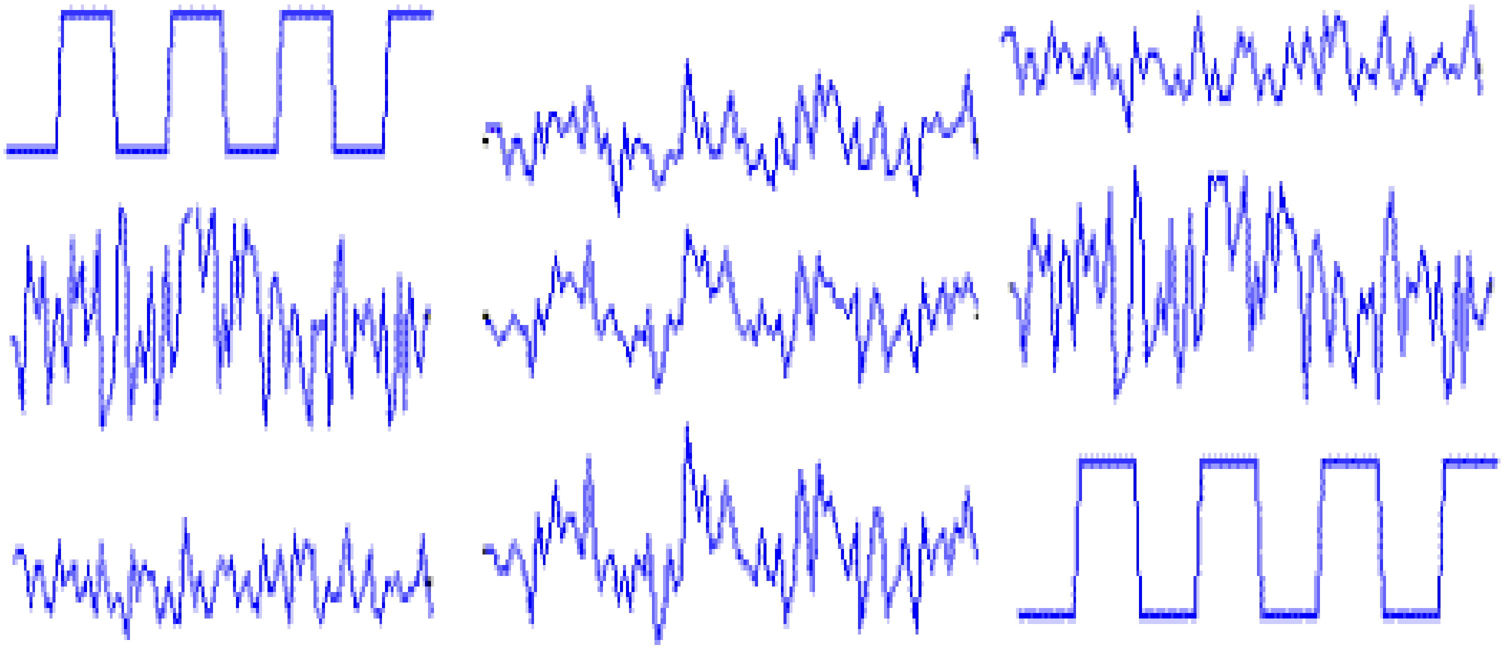
$$I(p_y) \approx C - \frac{1}{48}\sum_{i=1}^{M}\left\{4k_{iii}^{2} + k_{iiii}^{2} + 7k_{iii}^{2} - 6k_{iii}^{2}k_{iiii}\right\} \qquad (5)$$

互信息极小简化成了四阶累积量最大, 从而可以通过对四阶累积量的计算, 实现独立成份的分离。

（2）信息极大判据

理论分析表明, 如果把完成ICA的过程用一个运算网络表示，并在此网络的输出端, 引入相应的信源的累积分布函数为变换函数的一个非线性环节, 把转化为,则的熵最大就等效于式(5)互信息极小

4.ICA算法仿真实例：



原始信号　　混合信号　　ICA 分离信号

5. ICA理论研究方向

（1）固定点算法

（2）非线性ICA研究

（3）噪声ICA研究

（4）overcompleteICA研究

（5）子空间ICA研究

6.ICA应用研究

(1) 信号分离

(2) 图像去噪

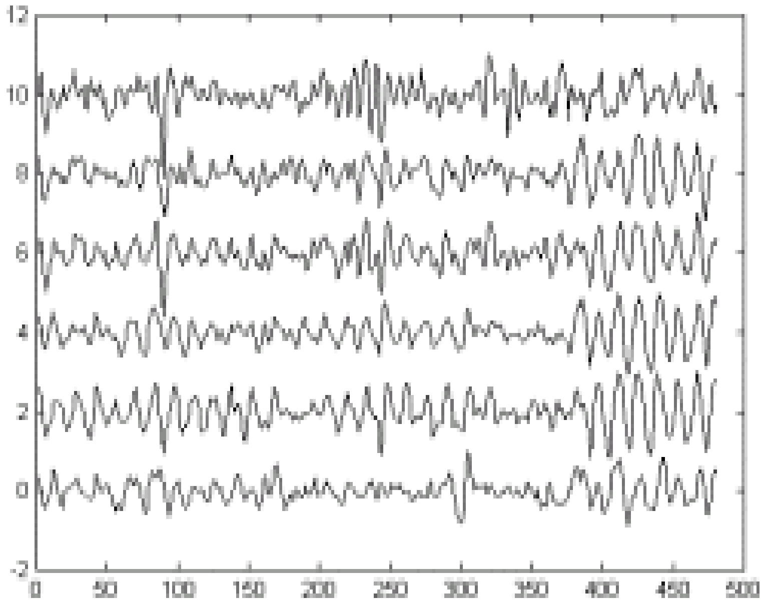
(3) EEG数据分离

(4) fMRI数据处理

7.本实验室取得的成就

(1)提出了基于互信息极理论的ICA梯度算法，并用于分离癫痫EEG信号

Y.Xu D.Yao, , Chinese Journal of Biomedical Engineering,
陈华富，尧德中， 信号处理, 2001)）



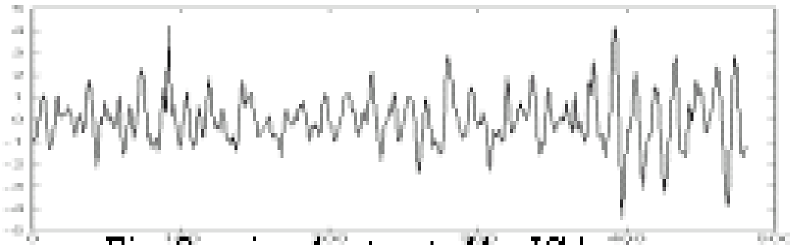


Fig. 2 a signal extracted by ICA.

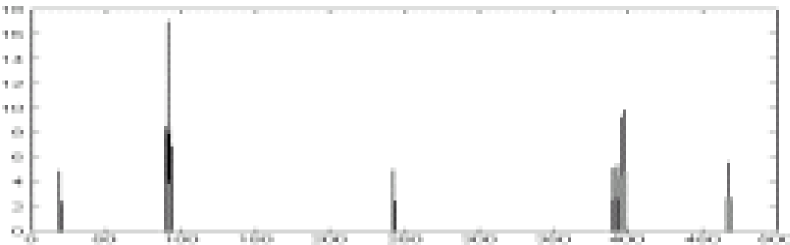
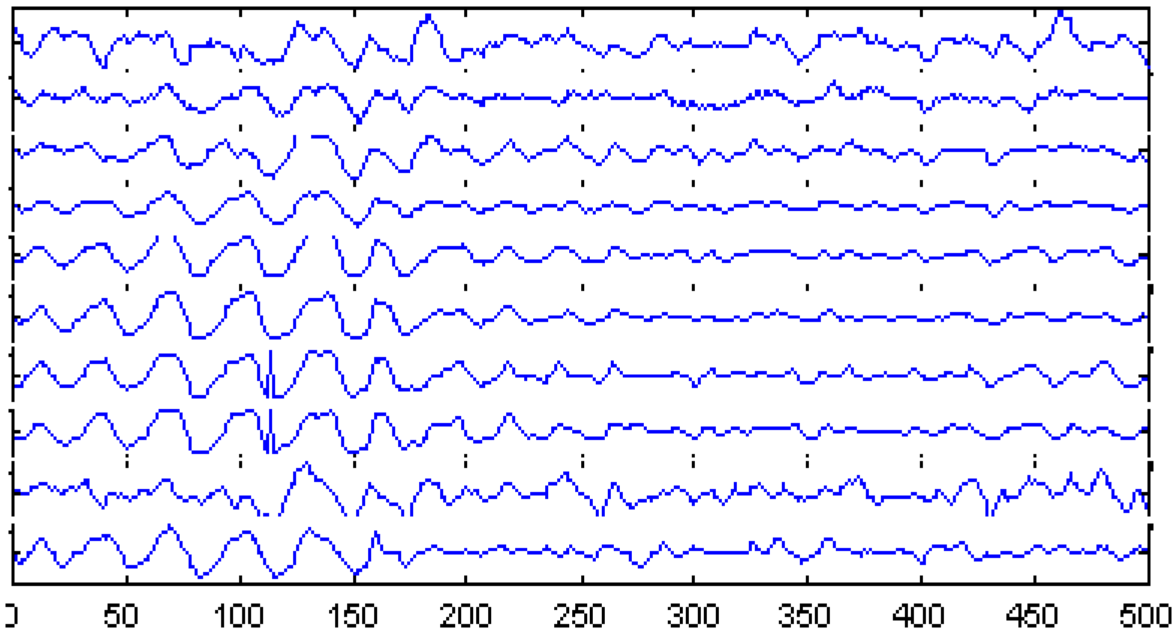
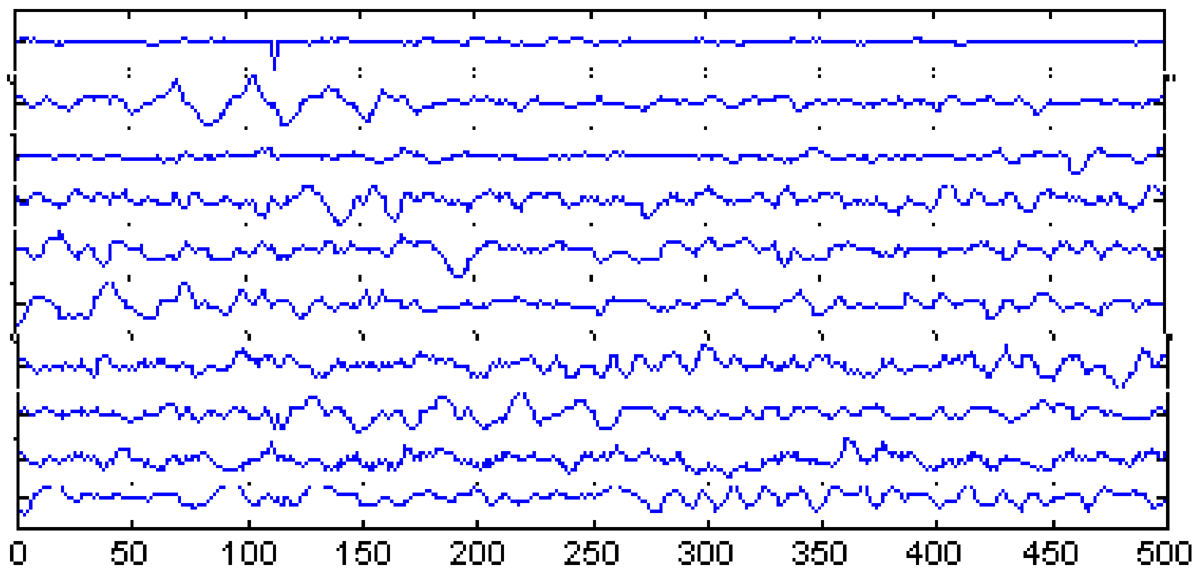


Fig. 1 the epileptic EEG.

Fig.3 the sharp waves extracted by non-linear energy operator



癫痫EEG
数据

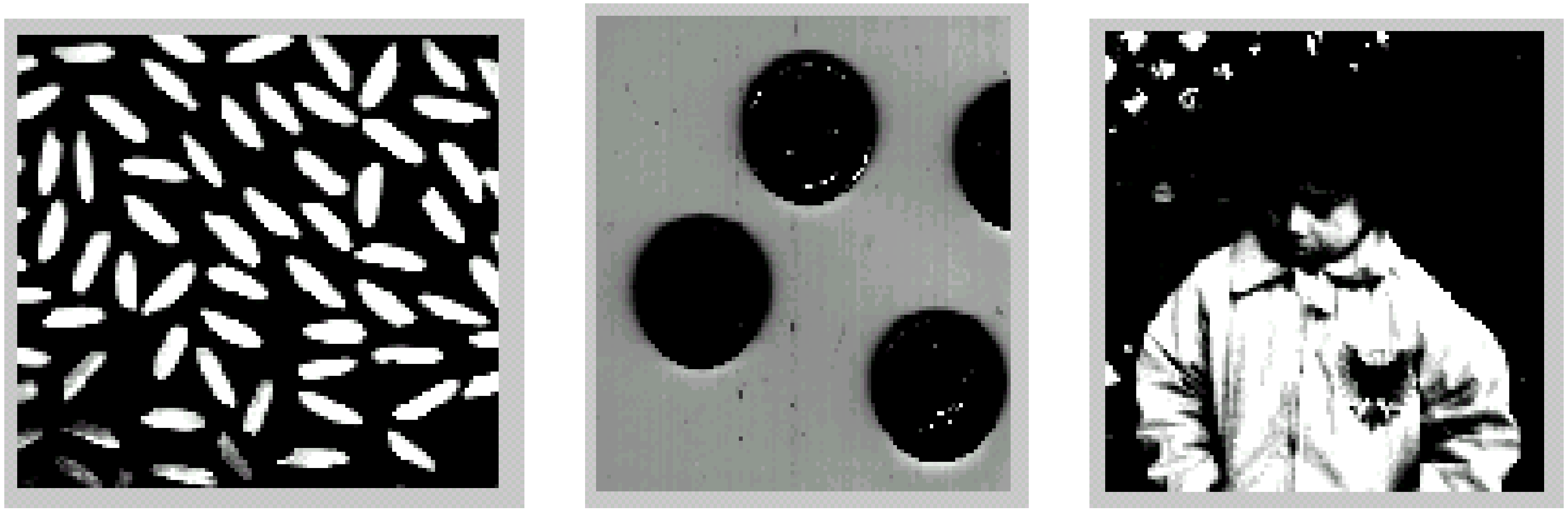


ICA分
离成
份

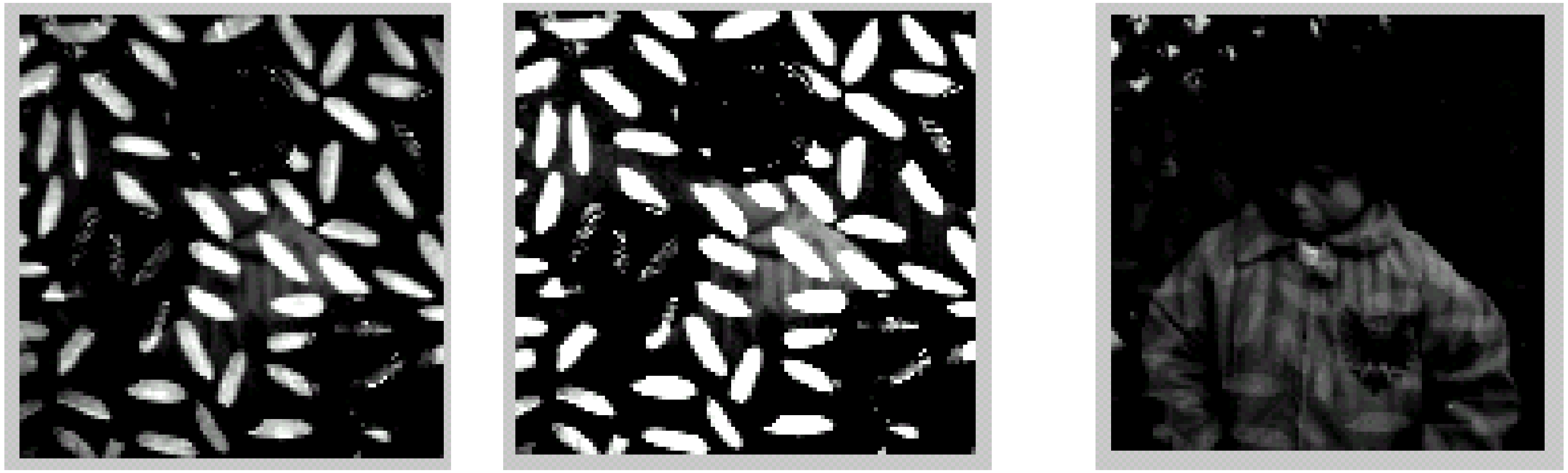
(2)提出了基于互信息理论的ICA信息极大快速算法，并用于混合图像分离（陈华富，尧德中， 信号处理, 2001)

ICA分离图像仿真实验

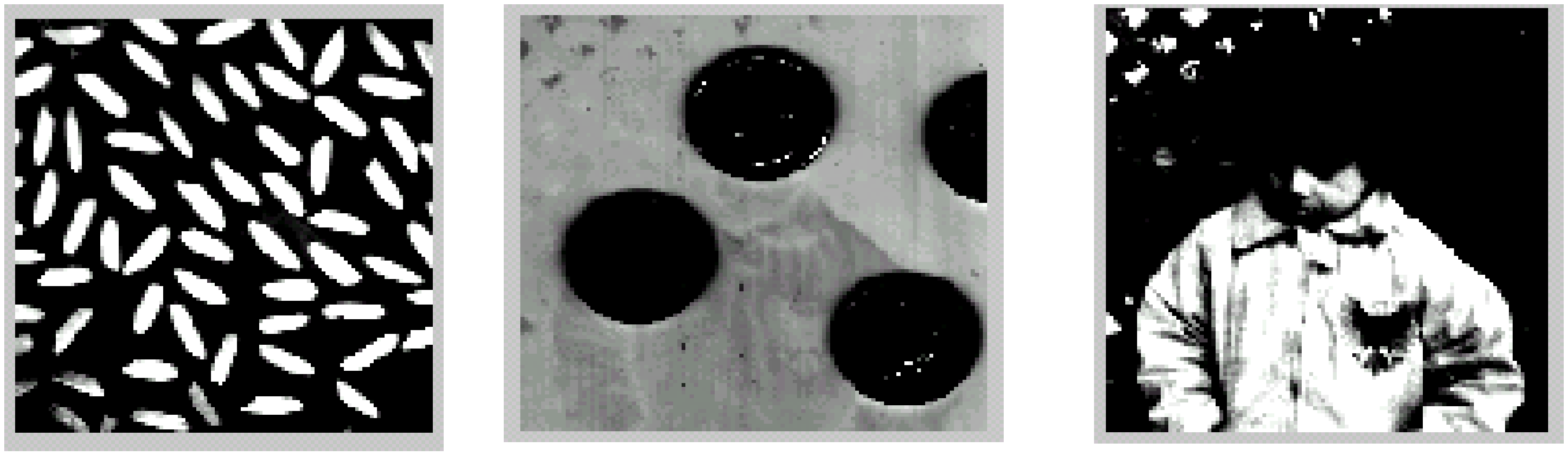
方法：通过二维图像与一维信号的相互转化再ICA分离



原始图像

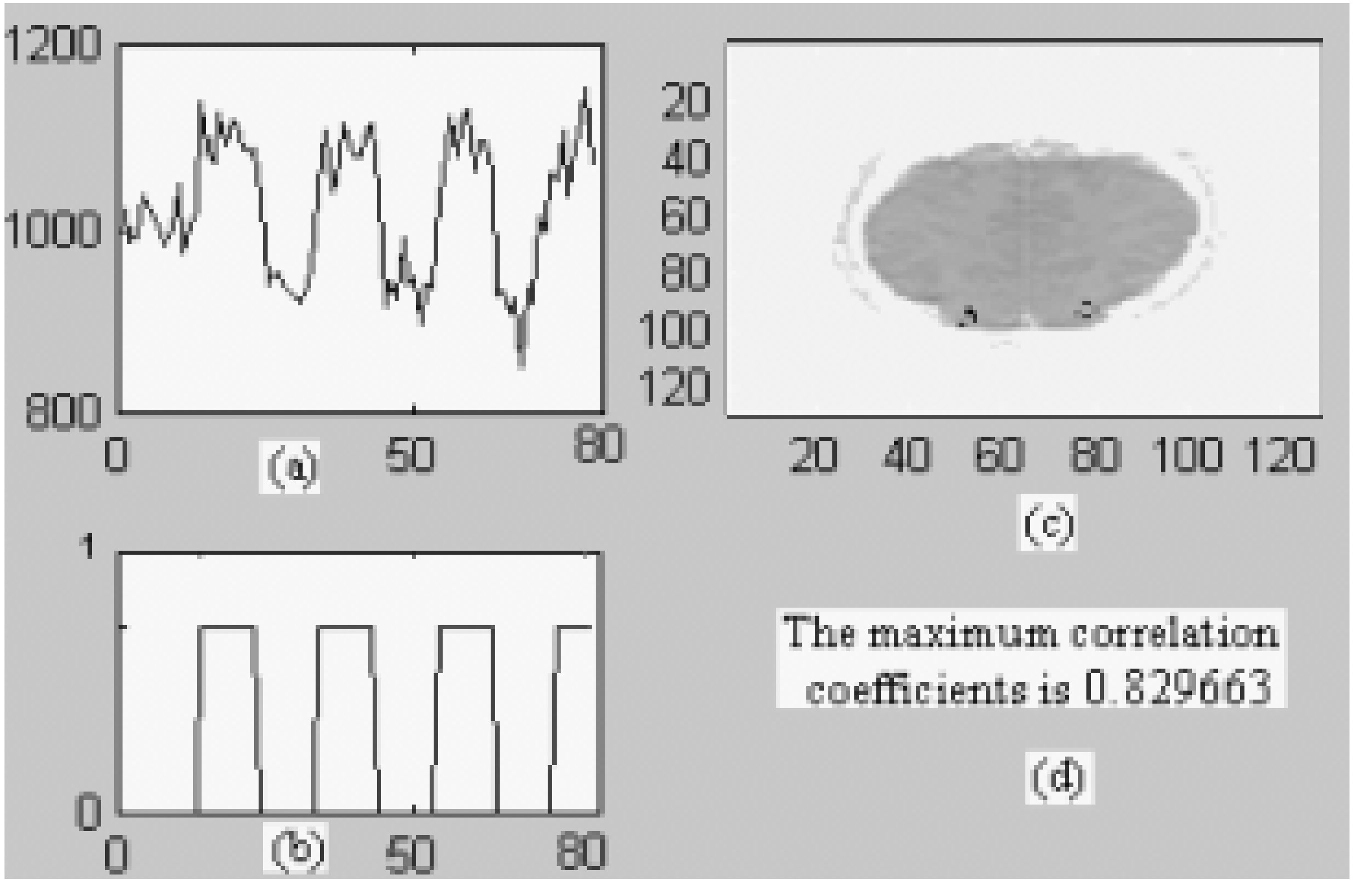


混合图像



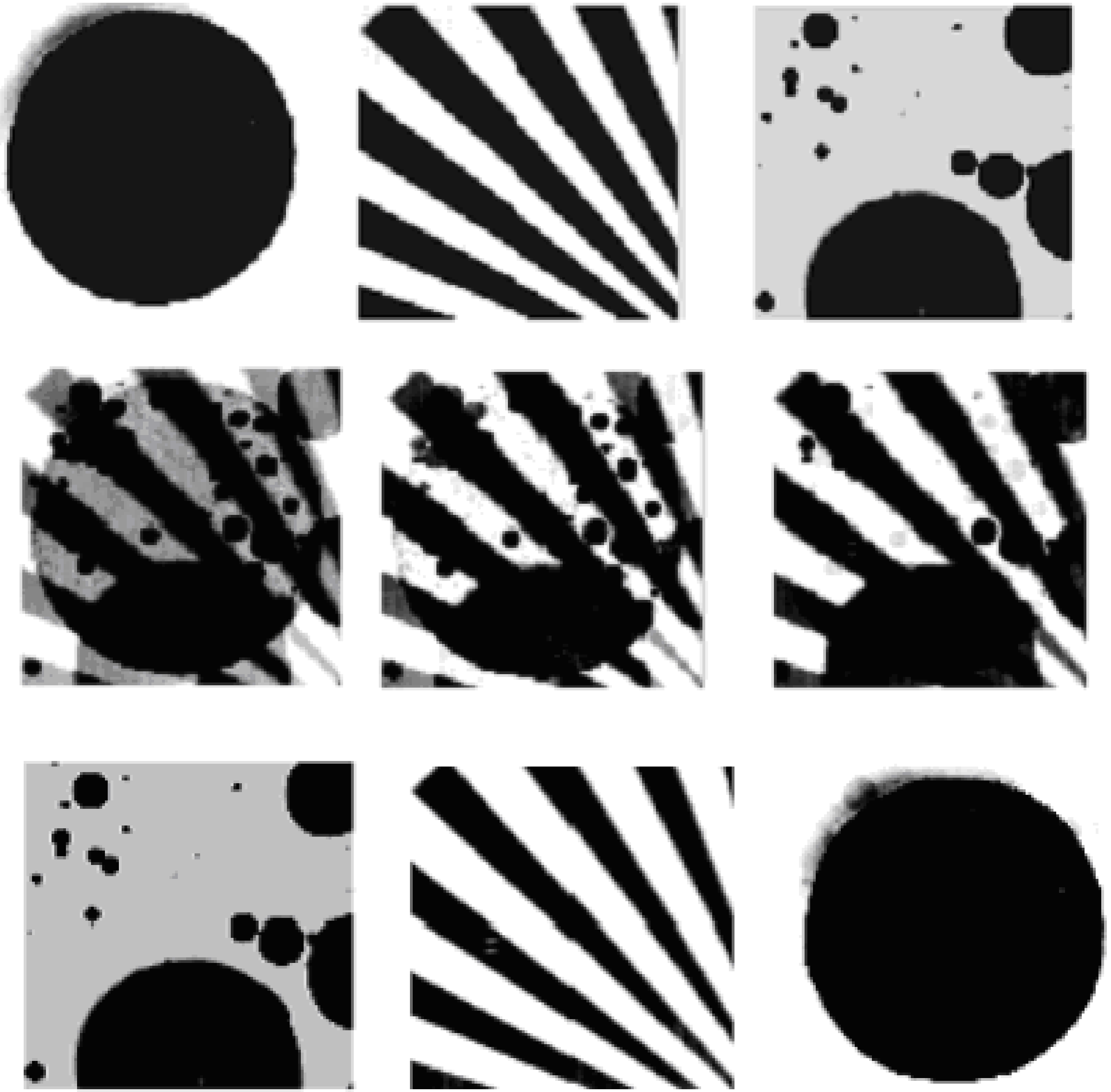
ICA分离图像

(3) 提出了基于固定点和梯度优势互补的组合算法及在fMRI中的应用 (Chen H, Yao D.ICCCAS 2002）



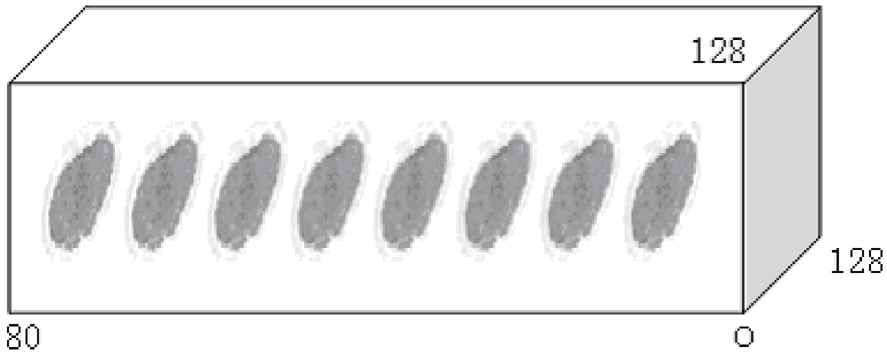
(4) 提出图像ICA分离理论和BFGS算法

Chen, Yao et al
Neurocomputing
submitted

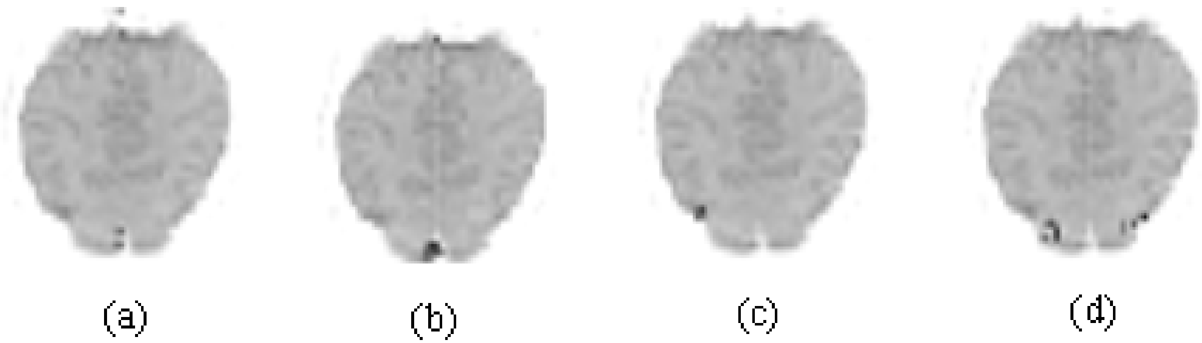


1) 图像仿真实验

5）图像ICA在fMRI中的应用

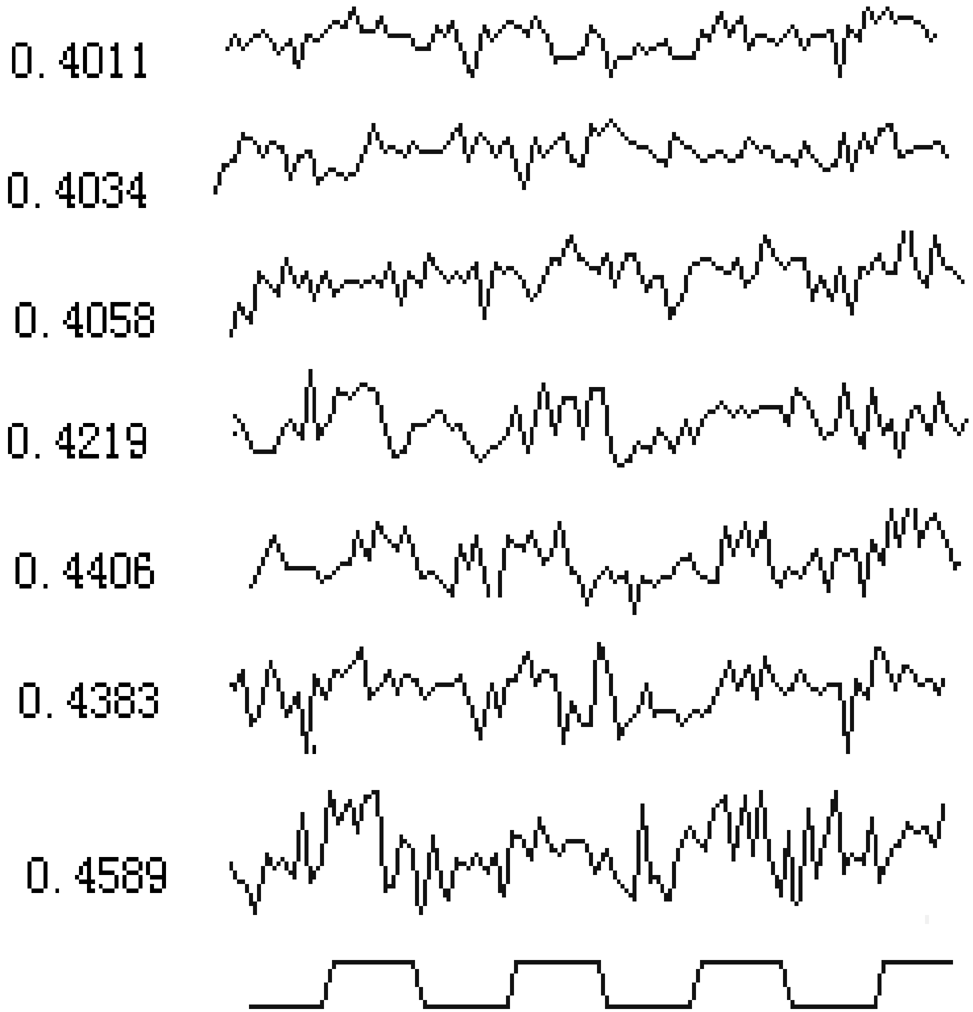


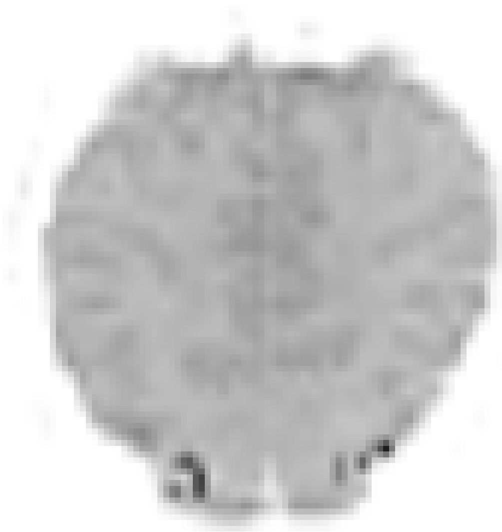
数据模型



分离图像

脑功能定位

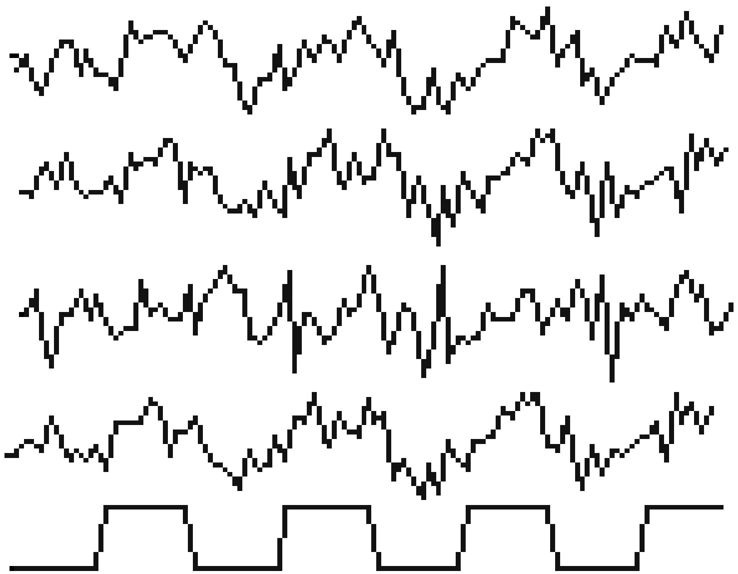




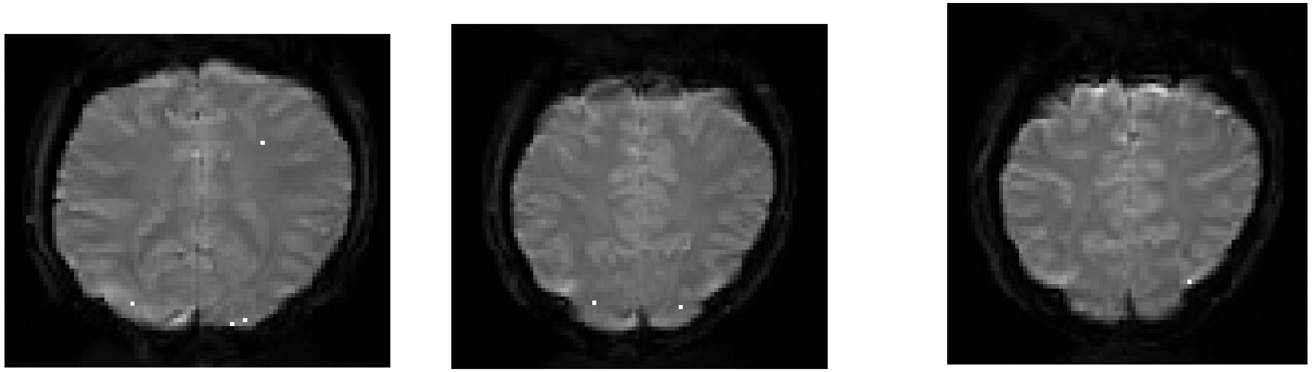
(9) ICA 分离fMRI数据中的脑功能活动成份

陈华富， 尧德中, 生物医学工程学杂志.(2002).

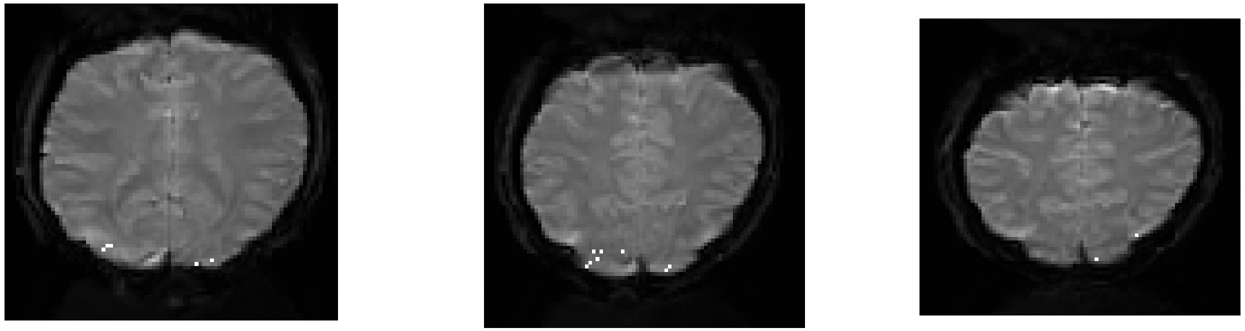
D Yao ,H chen IEEE Canadian Coference on Electrical and computer Engineering 2001



相关系数：0.4344, 0.4612, 0.0841, 0.5039.



相关法的fMRI成像结果



相邻两体元ICA—相关法的fMRI成像结果

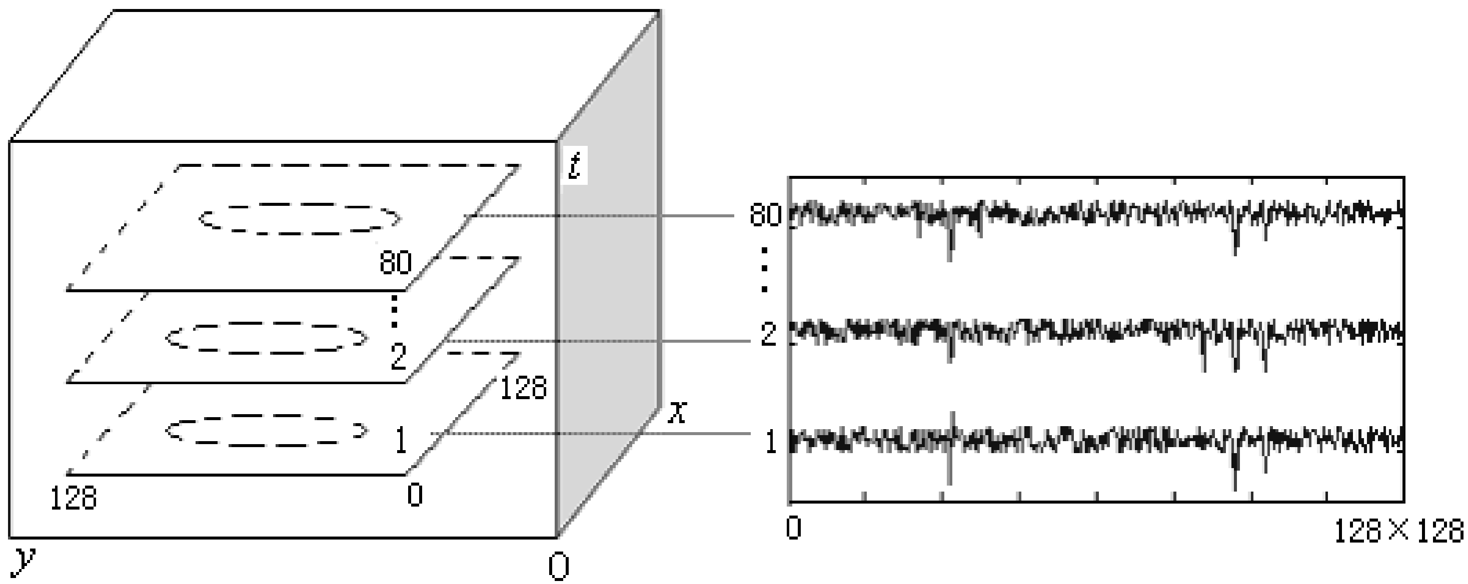
（10）基于fMRI时-空模型的ICA数据处理方法

SIM （Mckenown,1998)

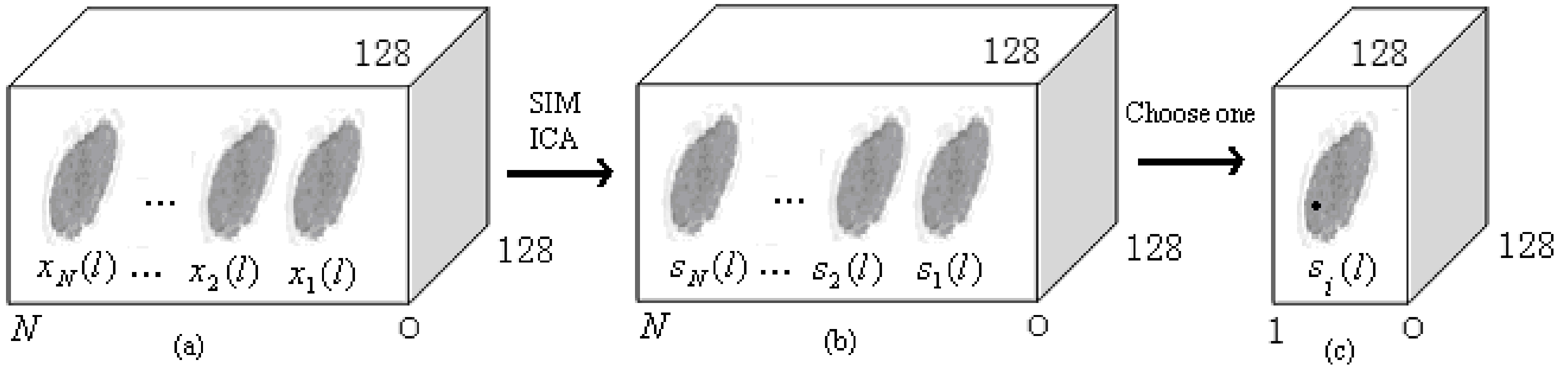
TIM (Chen, Yao et al ,science in china 2002)

Chen, Yao et al . Brain Topography, 2003

1)fMRI数据体描述



2)SIM及独立成份分析法示意图



The algorithm process of SIM

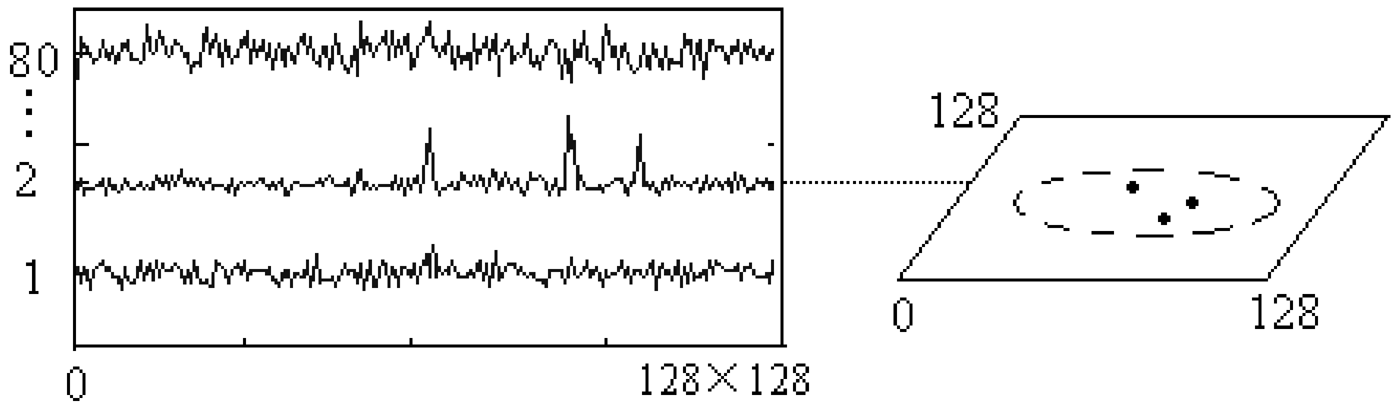
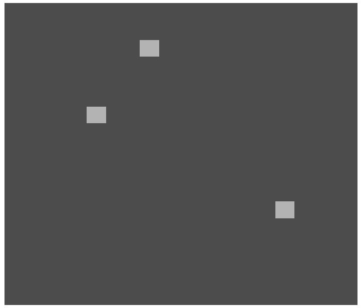


Illustration of SIM

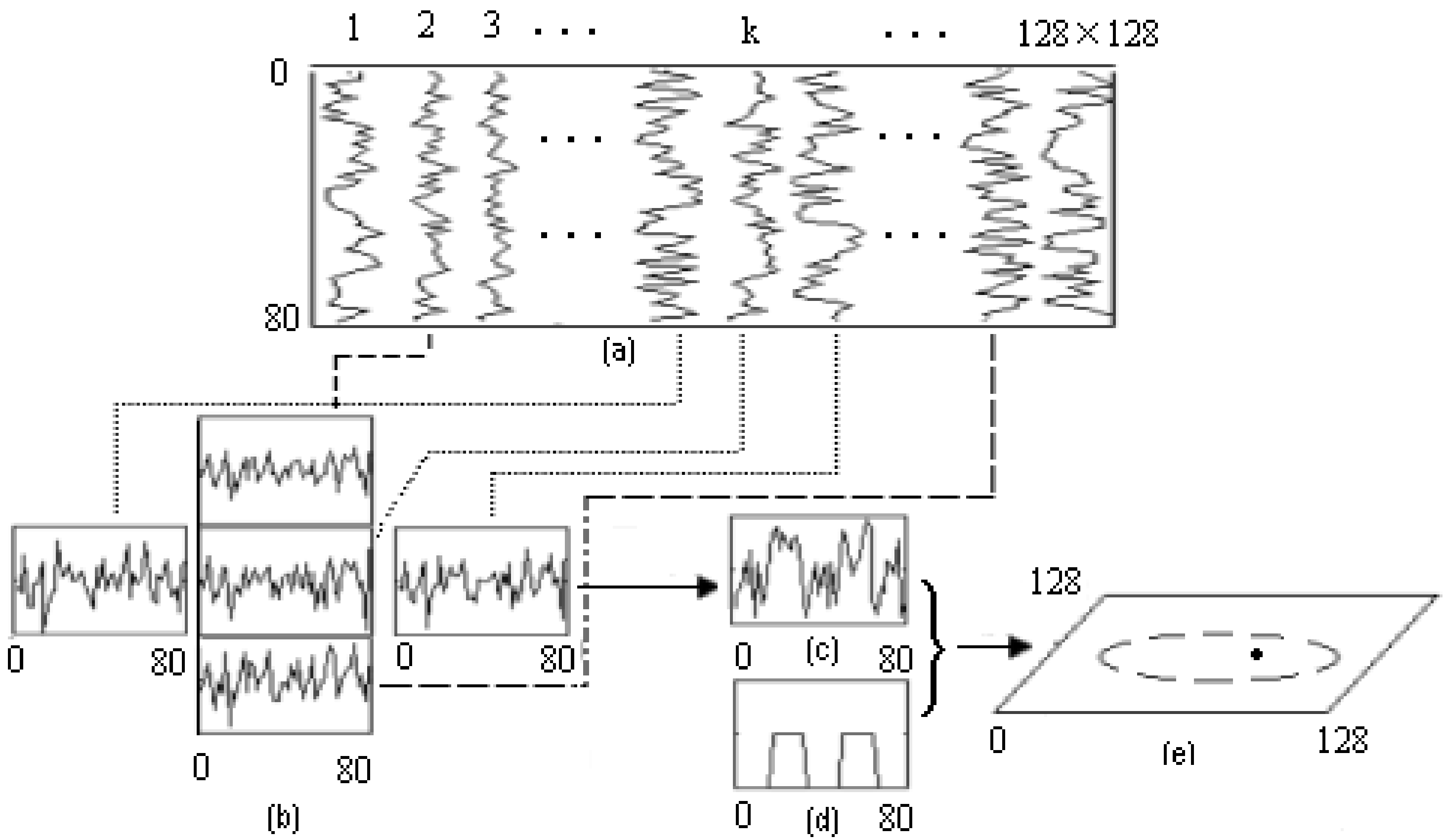
3）基于SIM的ICA方法对同步兴奋的成像效果



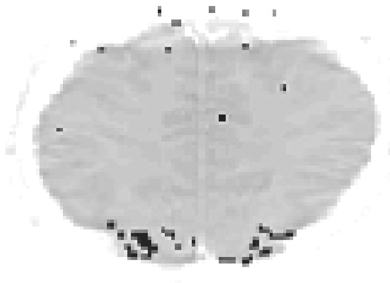
4）基于SIM的ICA方法对不同步兴奋的成像效果

5）基于TIM的ICA方法对不同步，同步兴奋的成像效果

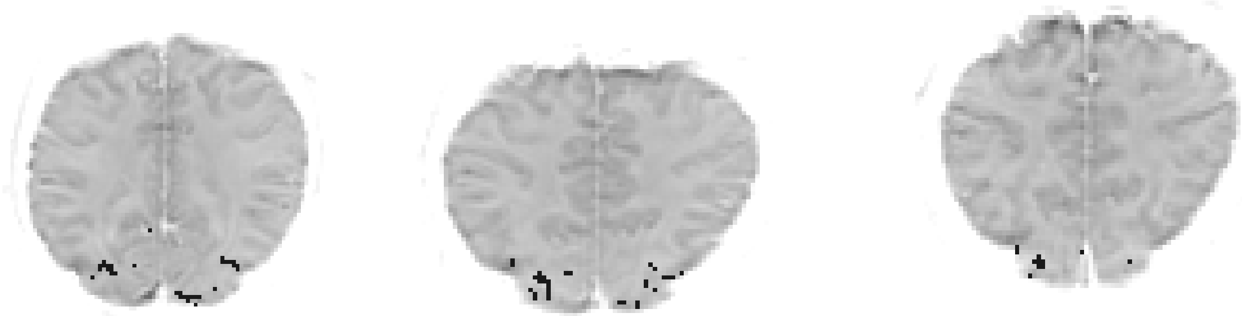
6)邻域独立成份相关算法TIM--示意图



7）TIM-邻域相关法处理实际 fMRI数据的结果(实验一）



阈值0.45



(阈值0. 55)

8）邻域相关法实验二的fMRI结果

阈值为0.43