Smart Medicine: Medical Big Data / AI with Innovative Applications in Patient Monitoring, Diagnosis, Prediction and Health Management:

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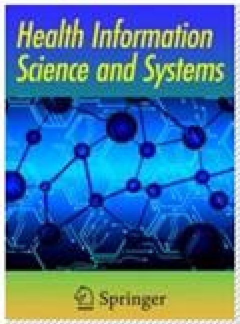

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Internet and Web Information Systems

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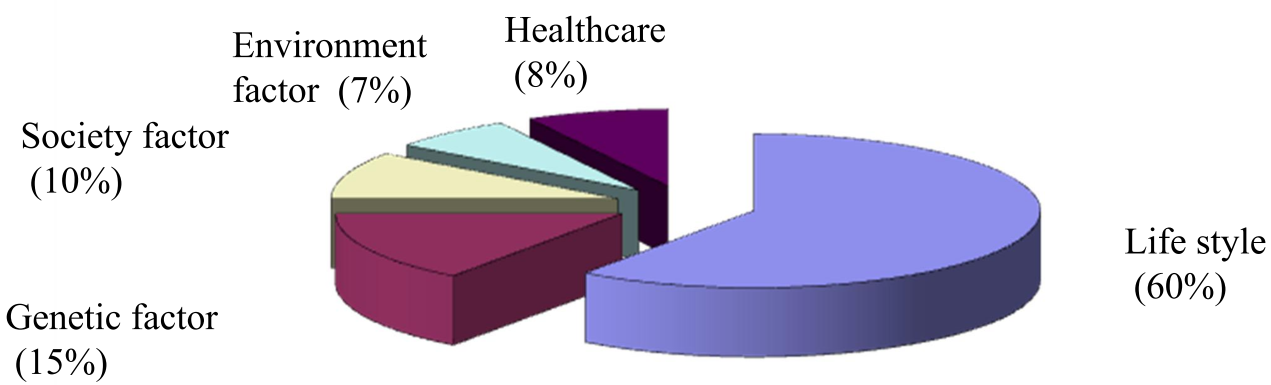


Which factor is the main reason for complex disease/health?

Living style

Mentality, diet , exercise…, rest (Sleep)

Environment,

Education, income, physical environment, pollution, …

Gene

Cancer gene….

Outline

1. Medical Big Data
2. Electroencephalograph (**EEG)** Data Analysis for Mental Health
3. Electrocardiogram (**ECG**) data analysis for ICU/Surgery Monitoring and Prediction
4. Summary and Future Work

1. Medical / health big data

"Big Data" period of Healthcare

Medical health big data

“Big Data”period of Healthcare

Medical/health complex data types

- **Text** Medline, electronic health records, web, forum, etc,
- **Time series** DNA, protein sequence, etc,
- **Three dimensions structures** Protein and other macromolecules,
- **Networks / Graphs** Regulatory network, metabolic network, protein-protein interaction, etc,
- **Images** fMRI, CT, X-ray, etc,
- **Data streams** **EEG, ECG**, etc,
- **Video** Surveillance video, etc,

Technical Support ——AI+Medicine
Three Pillars:

Big Data

Medical Big data

Computing Power

Parallel computing,

GPU, supercomputers,

cloud computing etc。

Algorithms

Machine learning, deep

learning etc

Algorithm revolution

Artificial Intelligence in Medicine

- **AI Powering Medicine**：

Providing sensing, learning, understanding, reasoning, decision making capability, solving the problem like human being。

- **AI Key technologies**：

Vision

Ability to see things。

Sound

Listening, converting sound to text

Language

Understanding language, semantics, meaning

Recognition ability

Human, events, location, and things and their correlation/relationships

Applying AI in medicine: human-machine /machine-machine communication, deep sensing/ understanding, fast data processing and reasoning, saving doctors’ time for concentrating more on patients, helping save or improve patients’ lives.

AI applications

Medical imaging
病灶识别与标注 / 三维重建
靶区自动勾画与自适应放疗

Health Management
营养学 / 身体健康管理
精神健康管理

Computer aided diagnosis
医疗大数据辅助诊疗
医疗机器人

Virtual Assistant
语音电子病历 / 智能导诊
智能问诊 / 推荐用药

Disease / Risk Assessment and Prediction
病灶基因测序与检测服务
预测癌症 / 白血病等重大疾病

Hospital Management
病历结构化 / 分级诊疗
DRGs智能系统 / 专家系统

Research platform
线上科研平台，提供GPU计算
算法框架 / 数据分析等服务

Drug Discovery
新药研发 / 老药新用 / 药物筛选
药物副作用预测 / 跟踪研究

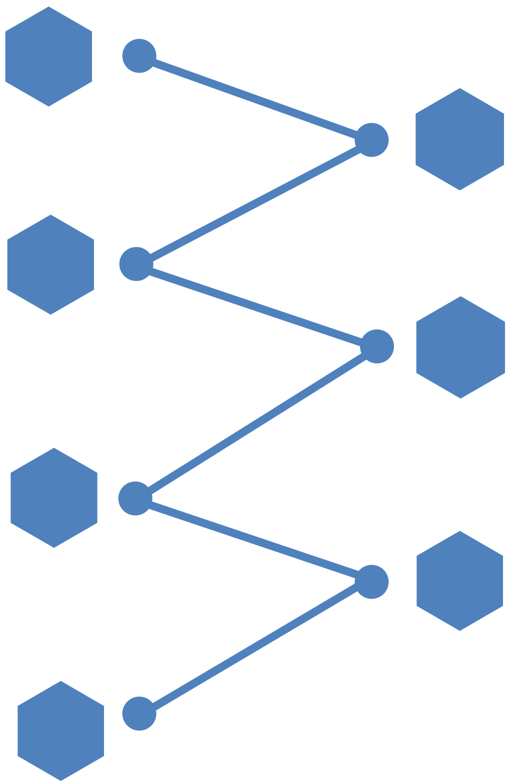
Our recent work

Medical imaging

EEG analysis

Drug Discovery

Aging care / elderly health



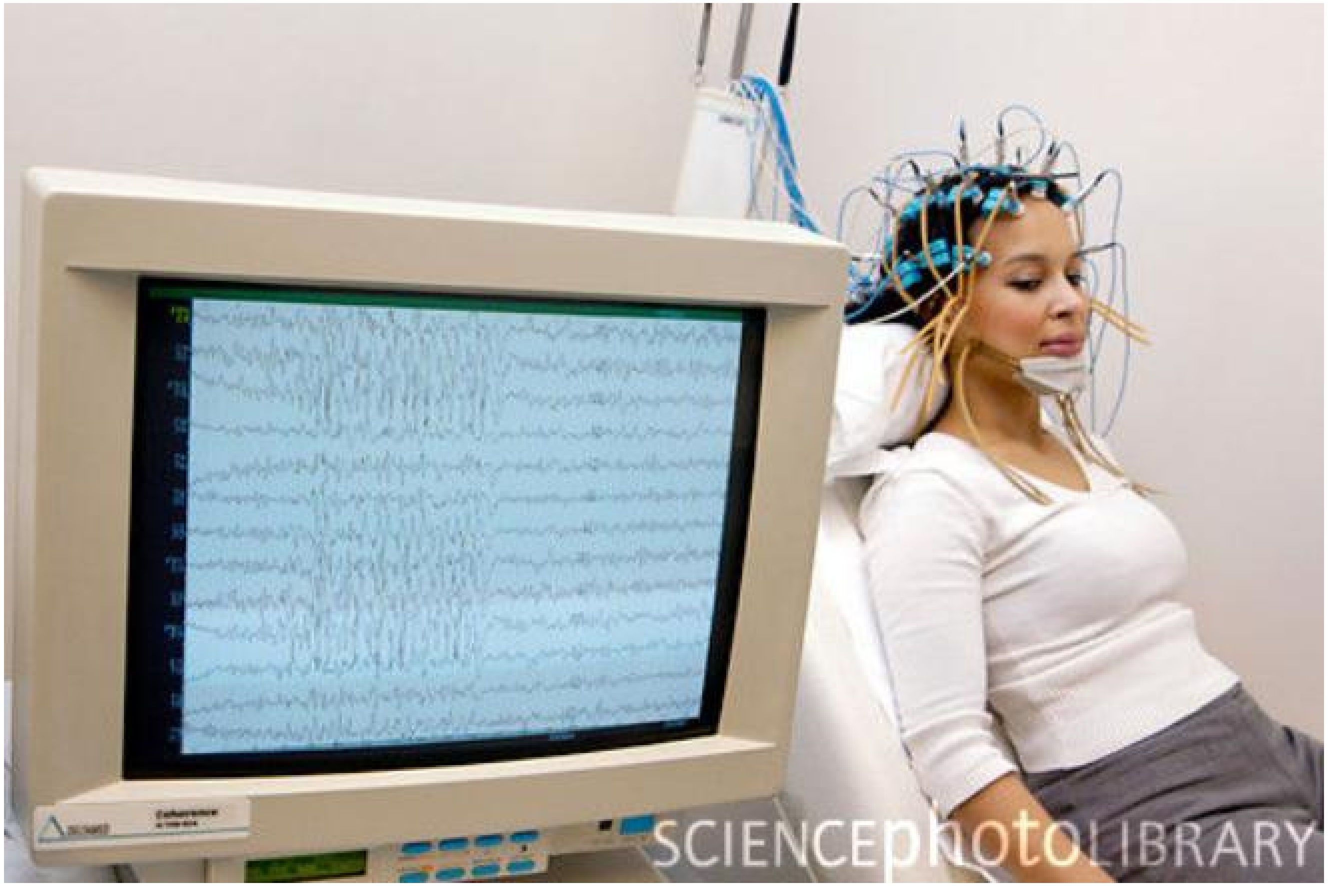
TCM

ECG analysis

Children's Health

2. Electroencephalogram (EEG) data analysis & Mental health

EEG signals

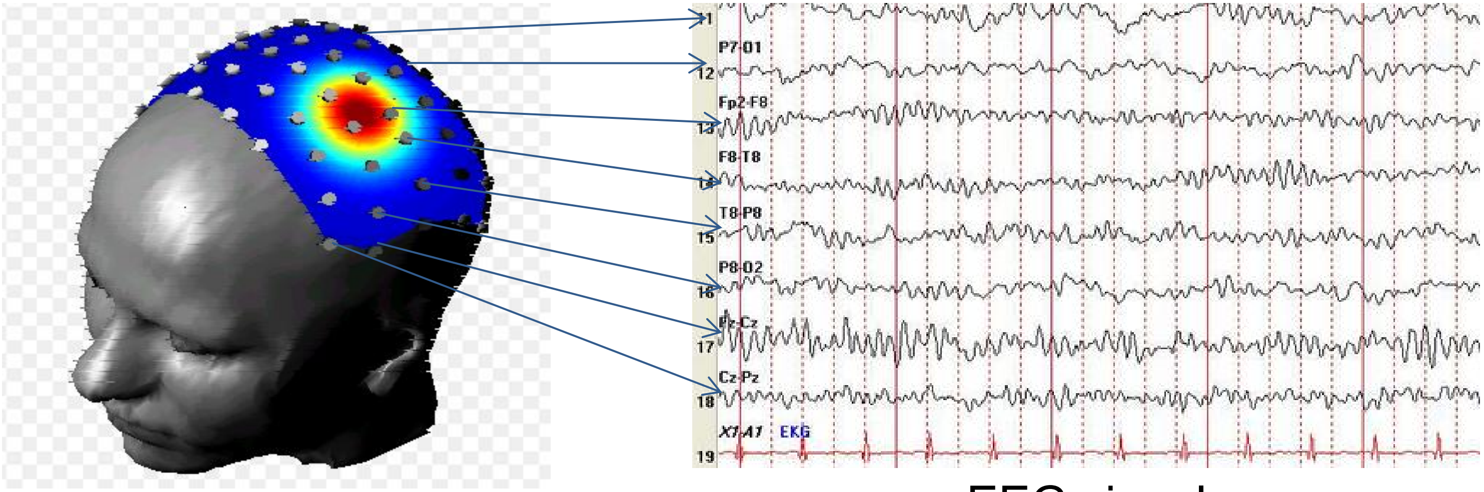


An example of EEG test

Brain signals

- When a person is thinking, reading or watching television different parts (**10B cells**) of the brain are stimulated. This creates electrical signals in brain, which, together with chemical reactions, let the parts of the body communicate.

- **Electroencephalography** (**EEG**) is the most used technique to capture brain signals for studying the functional states of the brain....



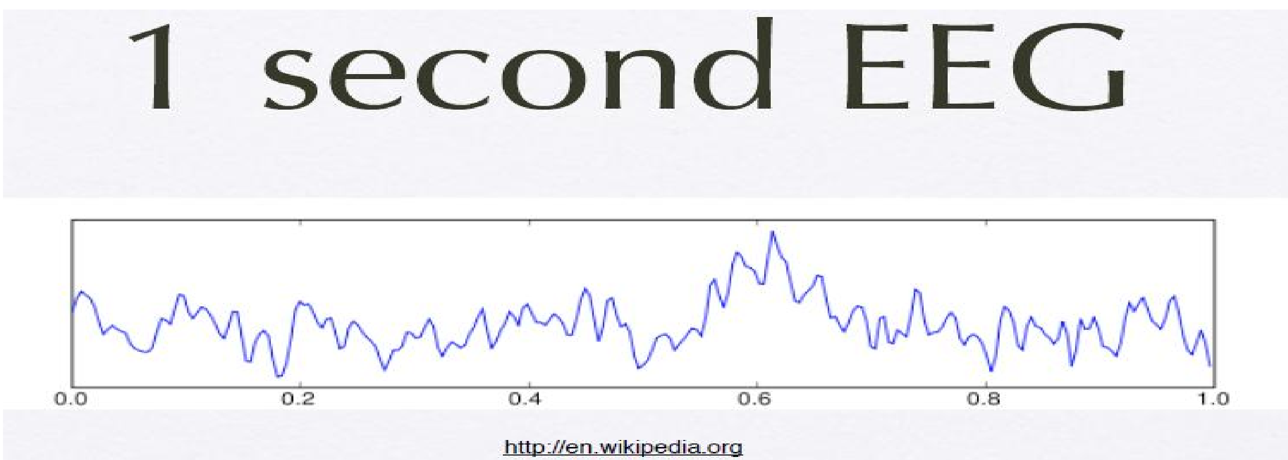
Human brain

EEG signals

Human Brain and EEG.

NATURE OF THE EEG SIGNALS

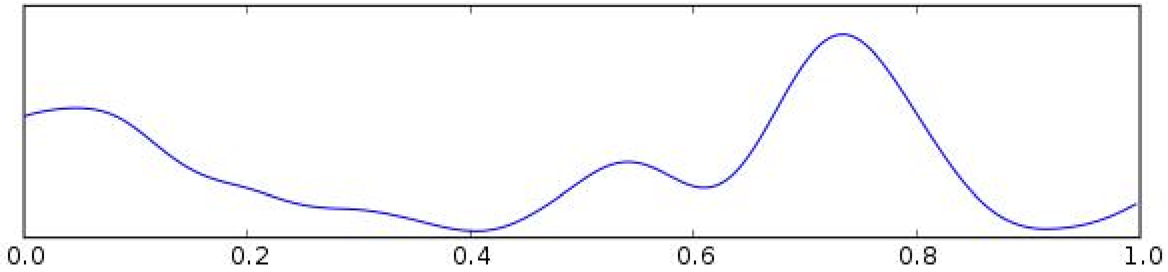
- **Frequency** is one of the most important features for assessing abnormalities in clinical EEGs and for understanding functional behaviours in cognitive research.
- Frequency Analysis helps to separate the different signals. EEG rhythms correlate with patterns of behavior (level of attentiveness, sleeping, waking, seizures, coma).



  - There are five types of frequency band in EEG described in the following slides:
  - **Delta (δ), Theta (θ), Alpha (α), Beta (β), Gamma (γ), Mu** (μ)

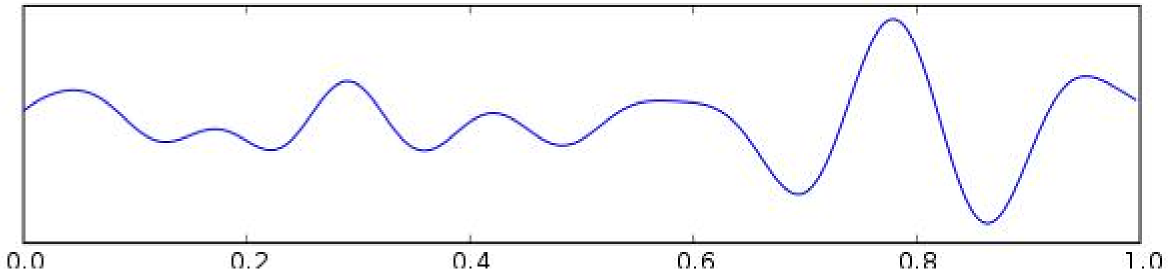
NATURE OF THE EEG SIGNALS

- **Delta (δ)**: frequency range up to 4 Hz. It is usually seen during sleep stages, especially "deep sleep".



Delta wave.

- **Theta (θ)**: frequency range from 4 Hz to 7 Hz. It may be seen in metabolic encephalopathy or deep midline disorders or some instances of hydrocephalus. Also associated with reports of relaxed, meditative, and creative states.



Theta wave.

Nature of the EEG signals

Alpha (α) : frequency range from 7Hz to 14 Hz. It emerges with closing of the eyes and with relaxation, and attenuates with eye opening or mental exertion or quiet waking or comma .

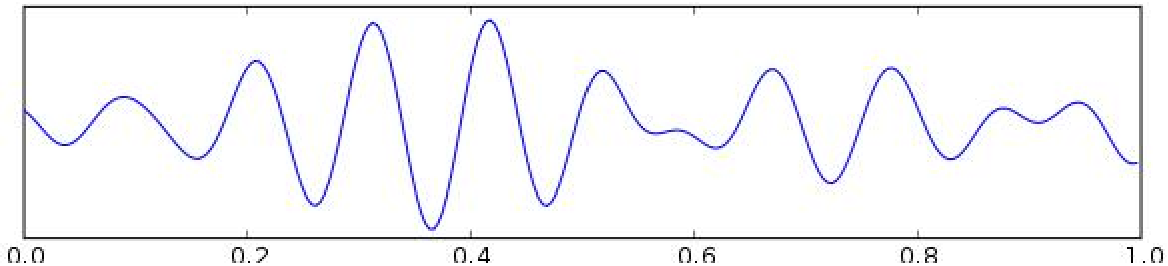


Fig. 11 (c): Alpha wave.

Beta (β) : frequency range from 15 Hz to about 30 Hz. closely linked to motor behavior during active movements and also associated with active, busy or anxious thinking and active concentration. Also associated with certain drugs or Pathologies.

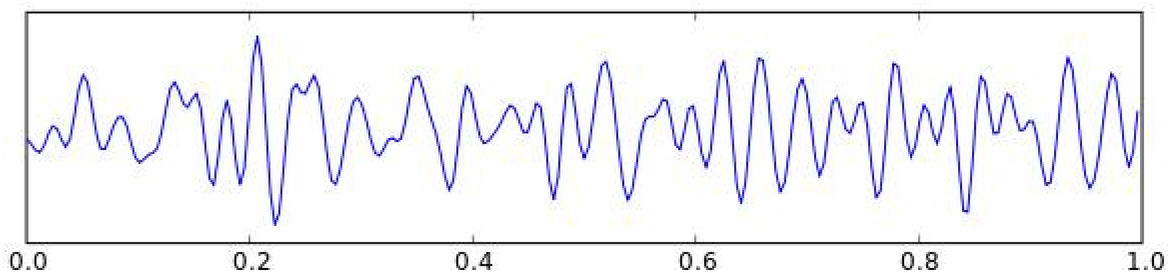


Fig. 11 (d): Beta wave.

Nature of the EEG signals

- **Gamma (γ)**: frequency range approximately 30–100 Hz. carrying out a certain cognitive or motor function, epileptic seizure tec.

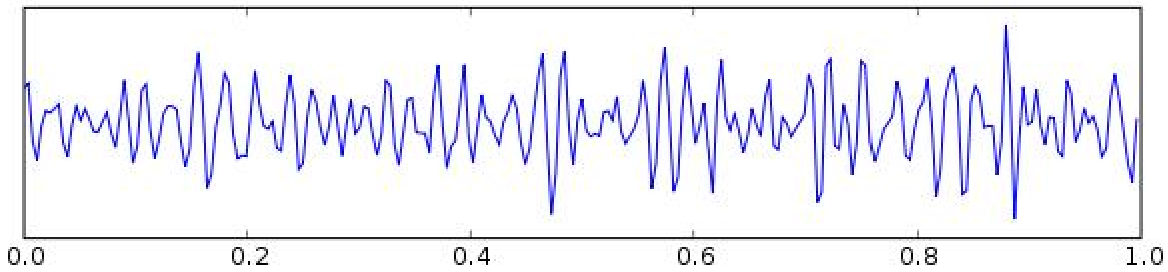
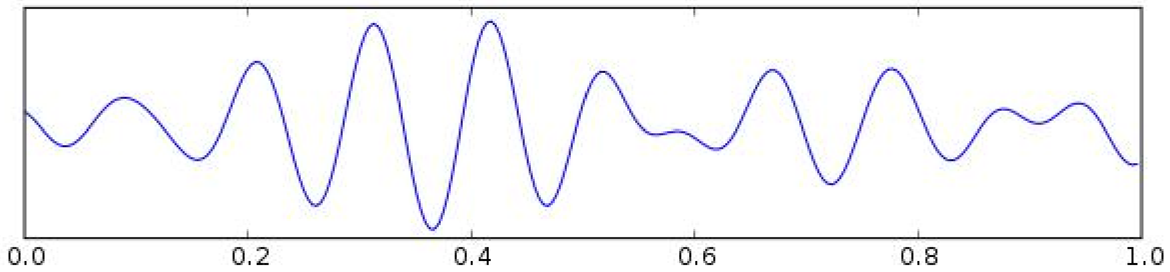


Fig. 11 (e): Gamma wave.

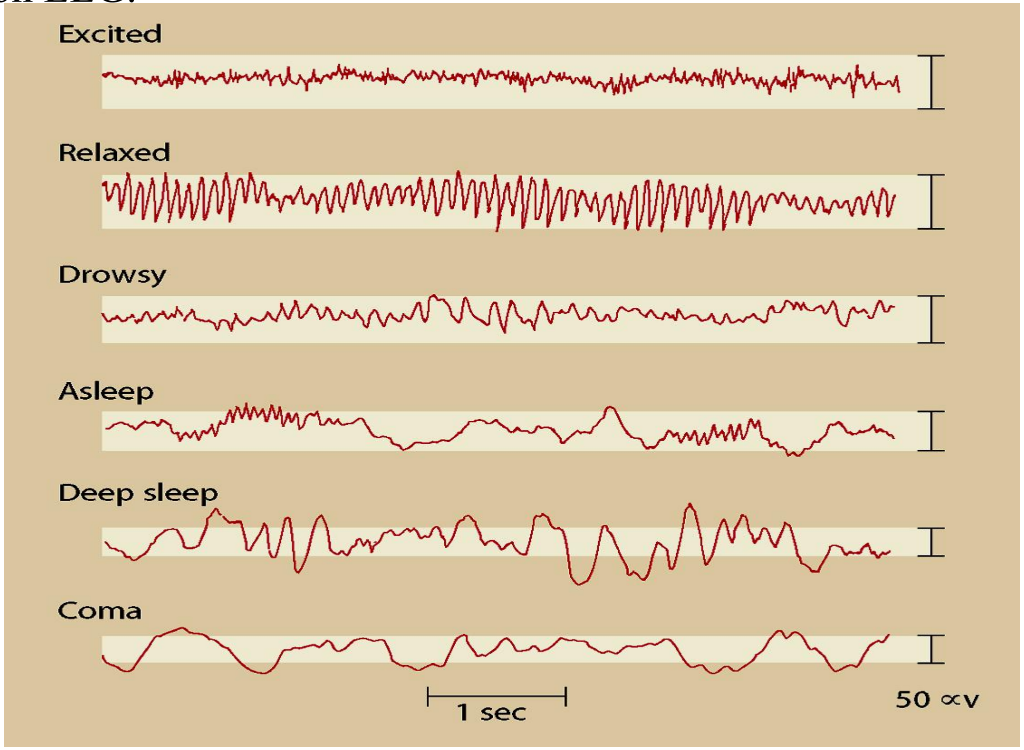
- **Mu** (μ) wave ranges 8–13Hz. Used to study neural development such as autism spectrum disorders (ASD).



Mu wave.

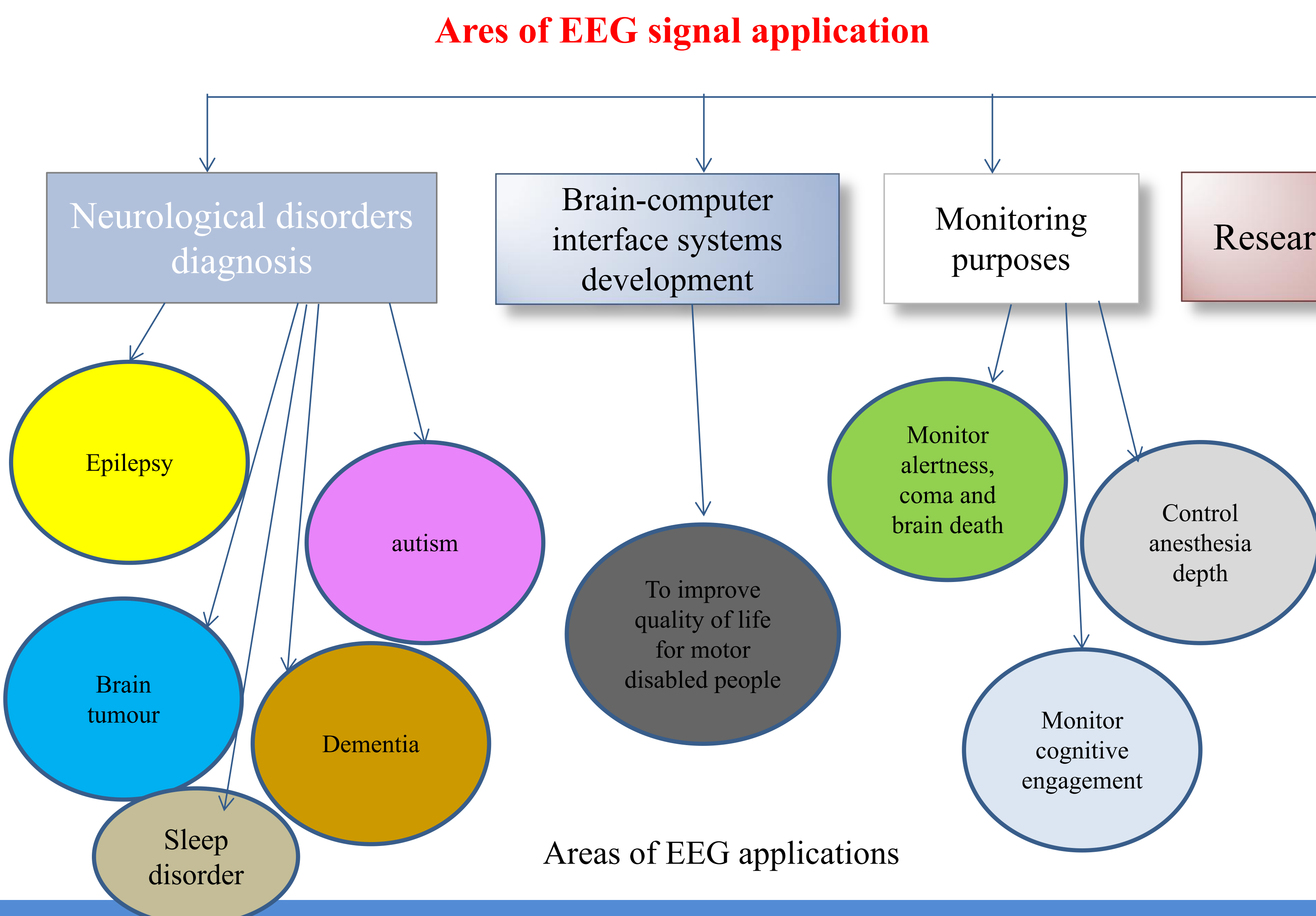
SOME EXAMPLES

- EEG potentials are good indicators of global brain state.
- An examples of different rhythmic patterns for different real -time activities as signature on EEG.



An example of EEG rhythmic patterns in various practical situations

APPLICATION OF EEG



Areas of EEG applications

Brain signals

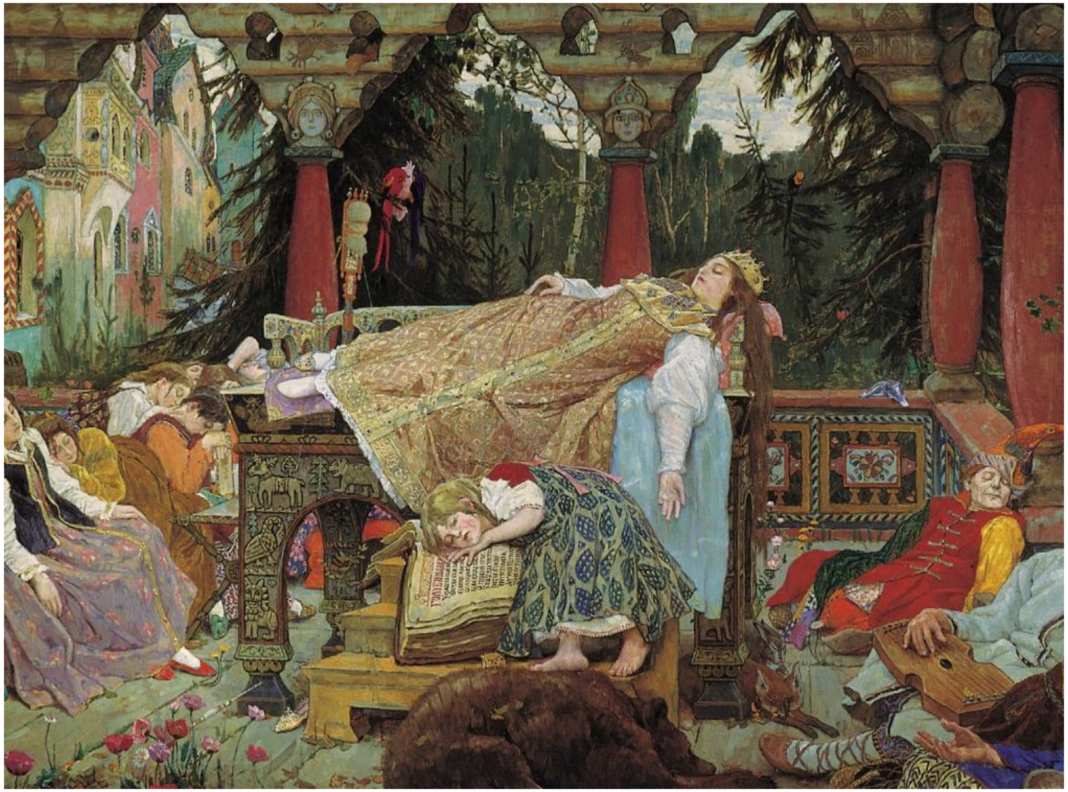
Take EEG first!

“I just smashed my feet,
why asking me to take EEG?”

“If your brain reacts, how can your feet be smashed”

Sleep

Sleeping Beauty



Sleeping Princess: An early 20th-century painting by Victor Vasnetsov

Sleep Introduction

- Sleep is closely related to people's daily lives, which accounts for **one-third** of the total life time.
- Sleep structure analysis and sleep disease diagnosis assisted through AI has become a widely expected solution.

1

Functions of sleep

Functions of sleep

1. Eliminate fatigue and restore strength

As body temperature, heart rate, blood pressure drop, respiratory and partial endocrine reduction, the basal **metabolic rate is reduced**, so that physical strength can be restored.

2. Protect the brain and restore energy

Insufficient sleep, manifested as irritability, agitation or lack of energy, distracted attention, memory loss, etc.; long-term lack of sleep can lead to hallucinations. Those who have **enough sleep are energetic, quick-thinking, and efficient**.

3. Other views in recent years

Enhance immunity, rehabilitate the body
Promote growth and development
Delay aging and promote longevity
Protect people's mental health
Conducive to skin beauty
The conclusion has yet to be confirmed!

2

Sleep EEG characteristics

REM

Eugene Aserinsky, one of Kleitman's graduate students, decided to hook sleepers up to an early version of an electroencephalogram machine, which scribbled across 1⁄2 mile (800 m) of paper each night. In the process, Aserinsky noticed that several times each night the sleepers went through periods when their eyes darted wildly back and forth. Kleitman insisted that the experiment be repeated yet again, this time on his daughter, Esther. In **1953,** he and Aserinsky introduced the world to "**rapid-eye movement**," or REM sleep. Kleitman and Aserinsky demonstrated that **REM sleep was correlated with dreaming and brain activity**. Another of Kleitman's graduate students, William C. Dement, now a professor of psychiatry at the Stanford medical school, has described this as the year **that "the study of sleep became a true scientific field."**

Sleep Stages

Awake stage

The consciousness is clear, and the alpha wave appears when the subject closes his eyes.

W

N2 stage

K complex wave and spindle wave appear deeper than N1 sleep

N2

REM stage

The EEG features are not obviousin this stage. The subjects can remember his dream when they are awakened in this stage .

R

N1

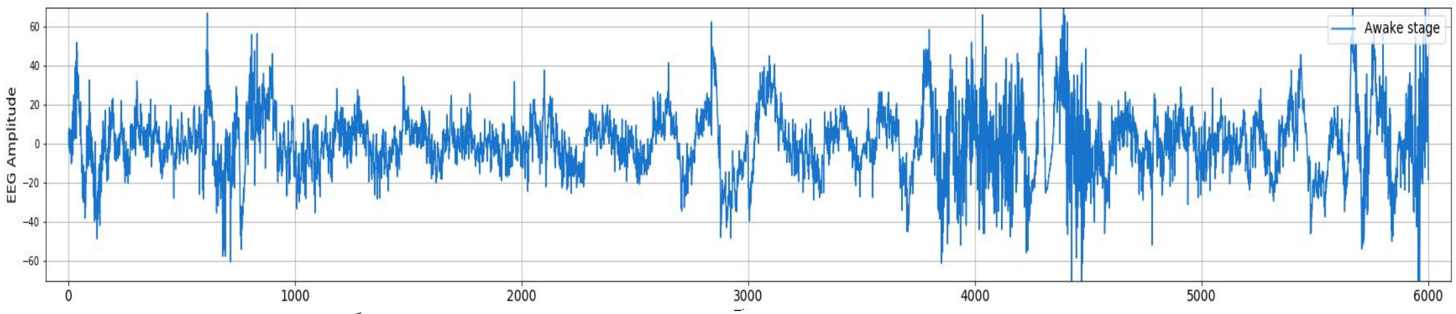
N1 stage

The N1 stage is a light sleep and does not last long. The alpha wave will decrease and a vertex sharp will appear.

N3

N3 stage

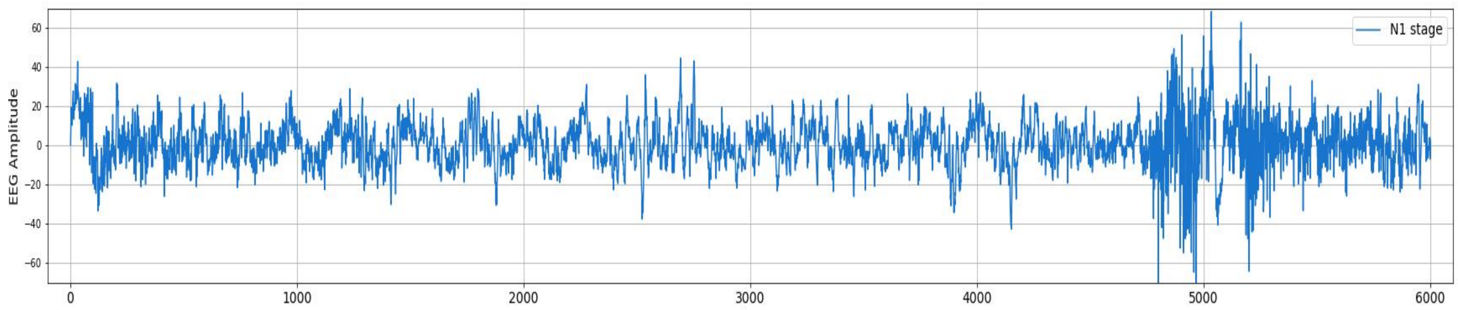
Deep sleep is not easy to wake up and you will feel tired when you wake up. Waveforms are generally low frequency waves.



Low amplitude mixed frequency

The W stage is characterized by low amplitude and mixed frequency EEG; **Alpha** waves and high tonic EMG may also appear.

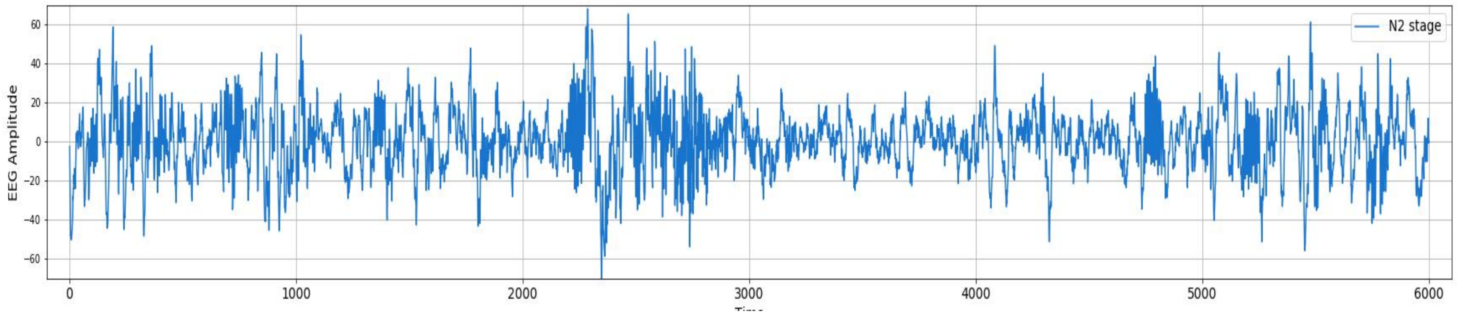
Fraiwan L, Lweesy K, Khasawneh N, et al. Automated sleep stage identification system based on time-frequency analysis of a single EEG channel and random forest classifier[J]. Computer Methods & Programs in Biomedicine, 2012, 108(1):10.



Alpha waves

In stage **N1,** the EEG signal has the highest amplitude, a frequency range of **2–7 Hz**, and the presence of **Alpha** waves in the EEG signal in less than half the epoch's duration.

Fraiwan L, Lweesy K, Khasawneh N, et al. Automated sleep stage identification system based on time-frequency analysis of a single EEG channel and random forest classifier[J]. Computer Methods & Programs in Biomedicine, 2012, 108(1):10.



Sleep spindle

Stage **N2** is characterized by the presence of sleep spindles (12–14 Hz) .

K-complex

K complex wave with duration longer than 0.5 second

Fraiwan L, Lweesy K, Khasawneh N, et al. Automated sleep stage identification system based on time-frequency analysis of a single EEG channel and random forest classifier[J]. Computer Methods & Programs in Biomedicine, 2012, 108(1):10.

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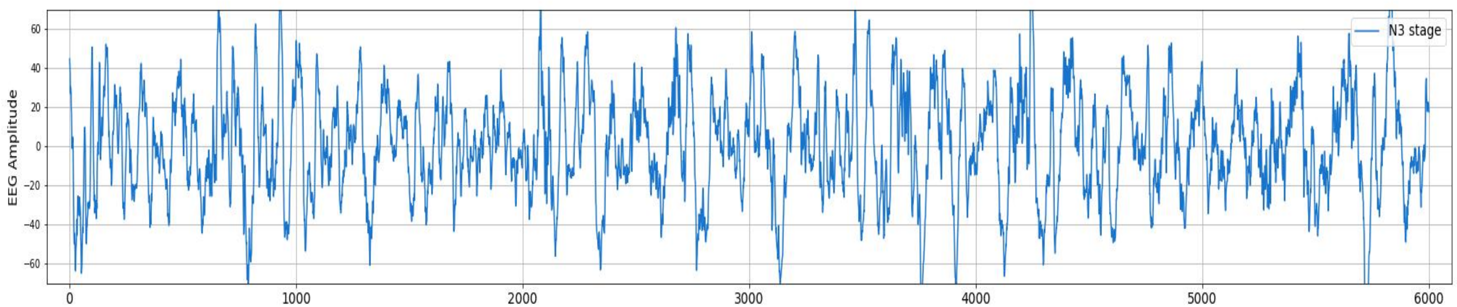
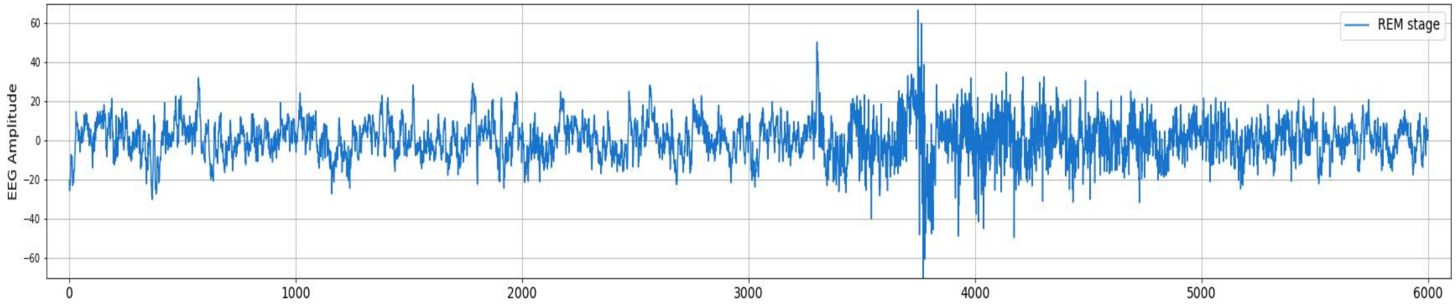


Delta waves

A low frequency wave of 0.5-2 Hz will occur, with an amplitude greater than 75 uV accounting for 20%-50% in the N3 phase.

Fraiwan L, Lweesy K, Khasawneh N, et al. Automated sleep stage identification system based on time-frequency analysis of a single EEG channel and random forest classifier[J]. Computer Methods & Programs in Biomedicine, 2012, 108(1):10.



Sawtooth waves

The **REM** stage shows low voltage, mixed frequency EEG, sawtooth wave-like pattern, low amplitude EMG, and high level EOG signal from both eyes.

Fraiwan L, Lweesy K, Khasawneh N, et al. Automated sleep stage identification system based on time-frequency analysis of a single EEG channel and random forest classifier[J]. Computer Methods & Programs in Biomedicine, 2012, 108(1):10.

Sleep Stages

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N3

N3 stage

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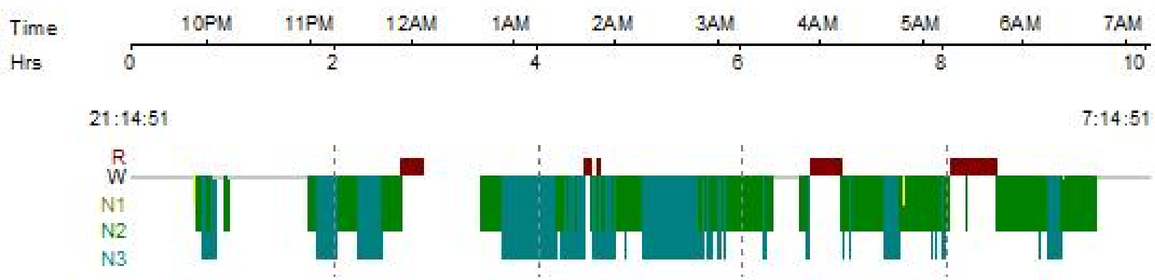
Sleep stages scoring

- Different sleep stages occur repeatedly during a whole night's sleep, follow a specific pattern, and account for a different proportion of sleep.
- Accurate sleep staging analysis can provide a basis for subsequent sleep analysis.
- The sleep quality of a subject can be assessed by, for example, statisticing different sleep stages to assess the distribution of sleep throughout each sleep stage. This also reflects the importance of sleep staging for sleep analysis.



Sleep staging multiple times

Normally, normal people will sleep for a certain period of time without interference

Sleep staging cycle

The awake stage, N1 stage, N2 stage, N3 stage and REM stage will appear multiple times according to a certain rule and constitute a whole night of sleep.

Different sleep staging functions

There are different functions in different sleep stages. For example, N3 stage sleep has a repair function on the body and internal organs, and REM stage sleep produces a dream.

Sleep stages scoring

Data representation

Data metric

Data classification

Visibility graph representation

Each sample point of the EEG data segment is determined according to the definition to be connected with other sampling points. After the connection is completed, a corresponding graph structure is generated.

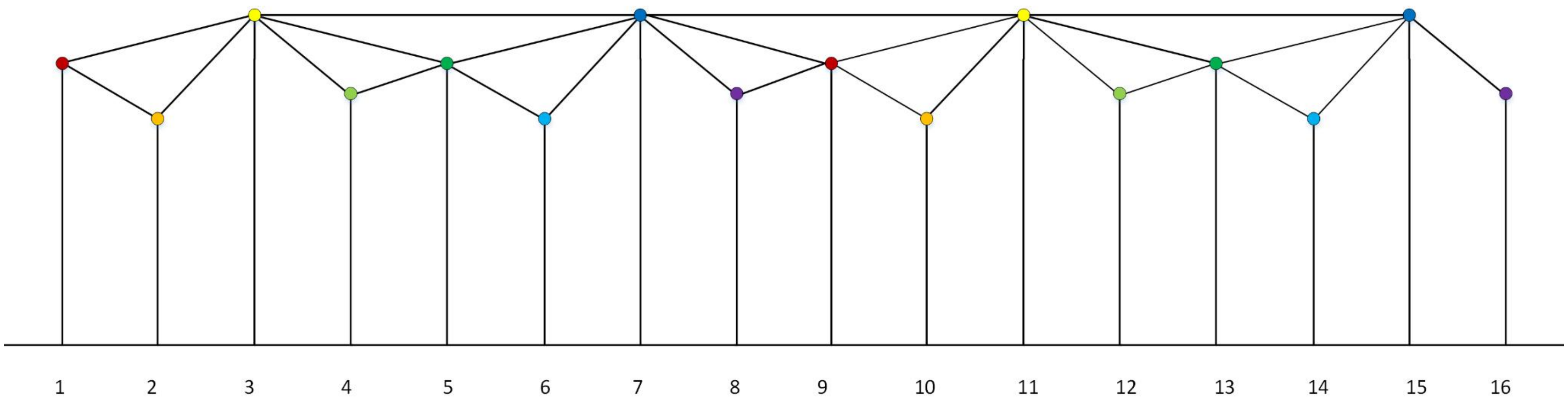
Graph metric

The adjacency matrix of the graph is measured, and the metric value is used as a feature of the corresponding EEG segment to distinguish the sleep staging in which the EEG segment is located.

Sleep stage scoring

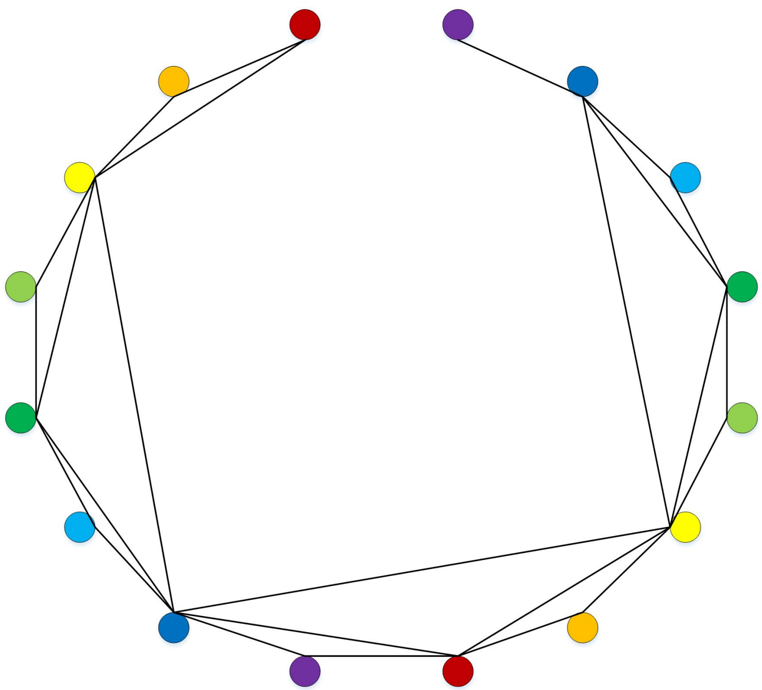
The data is staged according to different measurement results.

Sleep stages scoring



The above figure is an example. In the figure, a time series containing 16 sampling points is expressed in the form of a column.
When two points are visible to each other, there is an edge between the two points. When there is no visible between the two points, there is no edge between the two points.
In this way, all nodes are connected to build a graph.

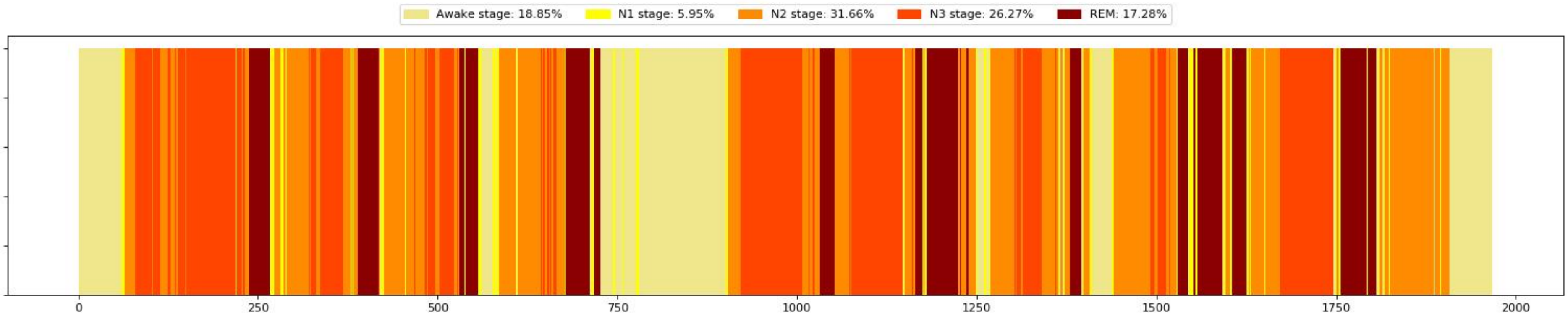
Sleep stages scoring



1. First, the EEG data is divided into EEG signal segments with a duration of 30 seconds.

2. Each sampling point of a time series segment is determined according to the definition to be connected with other sampling points. After the connection is completed, a corresponding graph structure is generated.

3. Then, the **adjacency matrix** of the graph is measured, and the metric value is used as a feature of the corresponding EEG segment to distinguish the sleep staging of the EEG segment.



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Different sleep staging functions

There are different functions in different sleep stages. For example, N3 stage sleep has a repair function on the body and internal organs, and REM stage sleep produces a dream.

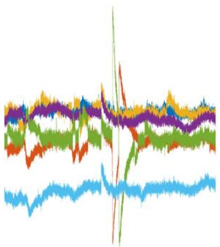
3. Sleep analysis and computer assisted diagnosis of sleep disease

Narcolepsy

[redacted]

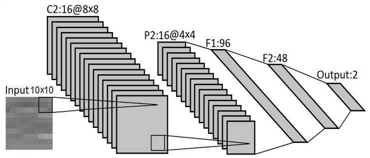
Lifelong sleep disorder:

- **Excessive daytime sleepiness** with irresistible sleep attacks
- **Cataplexy** (**sudden** bilateral **loss of muscle tone)**
- Hypnagogic **hallucination**, and
- **Sleep paralysis**. There are two distinct groups of patients： **narcolepsy with cataplexy** and **narcolepsy without cataplexy.**
- Narcolepsy affects **0.05%** of the population. It has a negative effect on the quality of life and can restrict them from certain careers and activities.



Two-dimensional representation of EEG

The data is divided according to a certain length of time. The horizontal axis of the two-dimensional representation represents time, and the vertical axis represents the length of the sample.



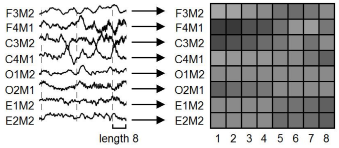
Classification

The model is trained through existing EEG data, and new EEG data is classified. Different two-dimensional representations are classified into different states.

Data collecting | **Data representing** | **Deep learning** | **EEG analysis**

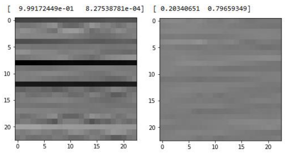
Collecting EEG data

Due to the many channels of EEG data acquisition, the high sampling frequency and the long acquisition period, it is difficult to find the law intuitively from EEG data.



Convolutional neural network

The model structure contains a convolutional layer, a pooled layer, and a fully connected layer.

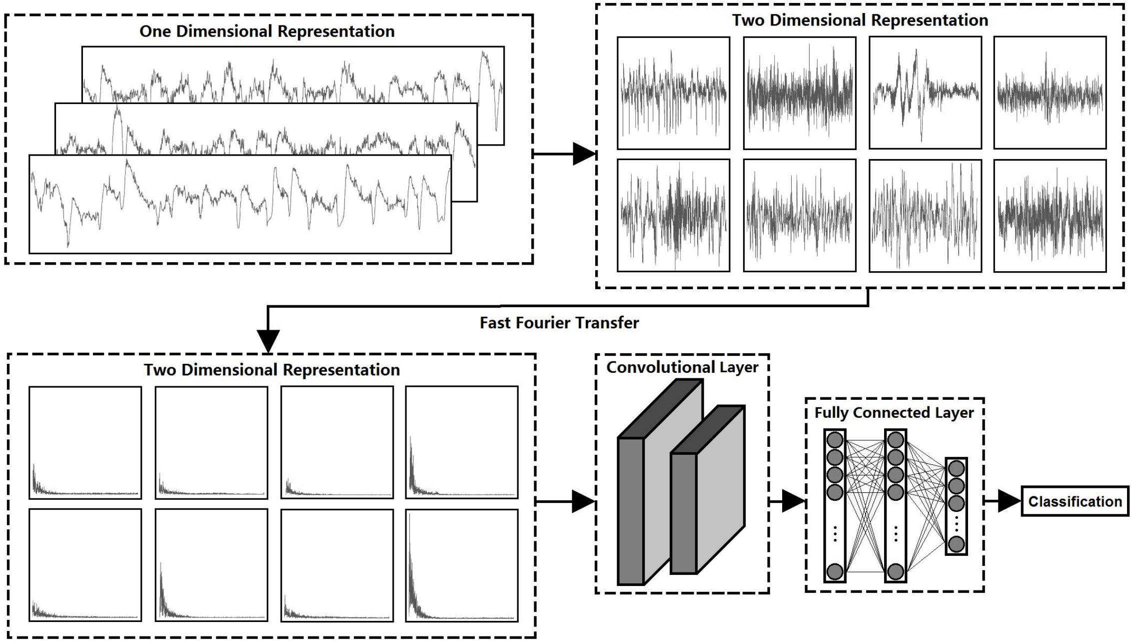


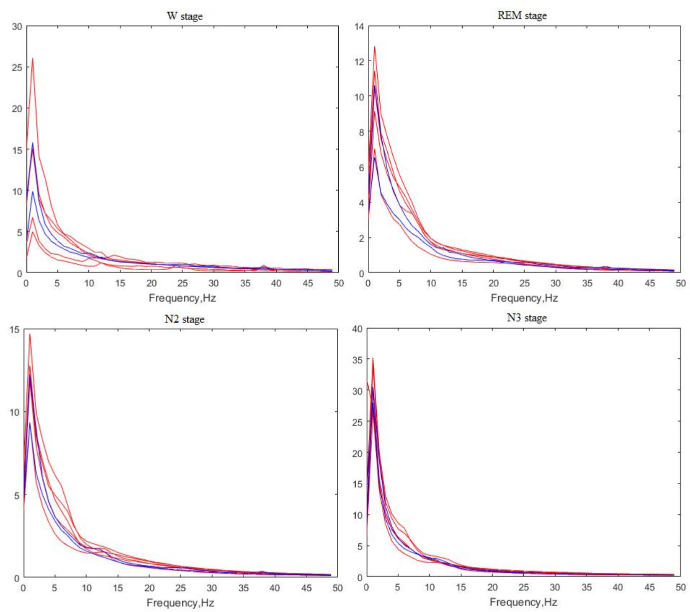
Sleeping stage analysis

(1) EEG Segment 2-d image

(2) Convert to frequency domain presentation

(3) Deep learning, CNN。





1. Subjects with small individual differences were selected, and the same sleep period and EEG of the same channel were compared.
2. The EEG data of the corresponding channel is segmented by a certain sampling length. This can be used to divide the subject's EEG into multiple segments for statistical analysis.
3. The Fourier transform is performed on the segmented EEG data to obtain the frequency information of each segment of EEG.
4. The results of the deep learning model test after data perturbation are compared with the results of the Fourier transform.
5. According to the above ideas, there is a distinguishable part between the **theta**（4-7Hz） wave in the **W and REM** stage, which is consistent with the conclusions of related articles in recent years.

ADD YOUR TEXT HERE

Analysis of narcolepsy based on EEG

Deep learning model

Generate adversarial example

analysis

The method of generating adversarial examples not only utilizes the superior classification performance of deep learning, but also provides an explanation for the problem of extracting features of narcolepsy in a disguised form.

Cooperative units and data sources

We have established cooperation with hospitals and medical research institutions.

The First Hospital of Hebei Medical University

We collaborated with the Institute of Mental Health, the First Hospital of Hebei Medical University, to study the direction of sleep abnormalities and depression.

Shanghai Mental Health Center

We work with the Shanghai Mental Health Center to study the direction of epilepsy and emotional recognition.

■ Obstructive Sleep Apnea/Hypopnea

Sleep apnea and hypopnea is the most common sleep disordered breath, which is associated with a series of health consequences, such as such as cardiovascular disease (CVD) and even sudden death.

(a) normal (b) hypopnea (c) apnea

Figure1: The nasal pressure airflow waveform:(a) normal waveform, (b) hypopnea waveform and (c) apnea wave form

Score criterion for sleep apnea and hypopnea:

- Apnea was defined as a ≥ 90% drop in respiratory flow for at least 10 seconds with breathing effort.
- Hypopnea was defined as a ≥ 30% drop in respiratory flow for at least 10 seconds, associated with ≥ 3% oxygen desaturation or arousal.

■ Datasets

Table 1
Detailed descriptions of datasets.

Dataset Attribute	FAH	CMH	Total
Subjects	405	45	450
Age	30-48	32-48	–
Categories			
Normal	165249	24436	189685
Apnea	163716	14435	178151
Hypopnea	86095	6374	92469
Severity			
No OSA	47	6	53
Mild	106	11	117
Moderate	85	9	94
Severe	167	19	186

- 200Hz nasal pressure airflow signals and 10Hz Spo2 signals are from Sleep Center of the First Affiliated Hospital (FAH), Sun Yat-sen University and the Integrative Department of Guangdong Province Traditional Chinese Medical Hospital (CMH) between January 2018 and December 2019.
- In the raw signal preprocessing step: all the records are split into the10-second-long segments.

■ Method and results

- **A bimodal feature fusion CNN**

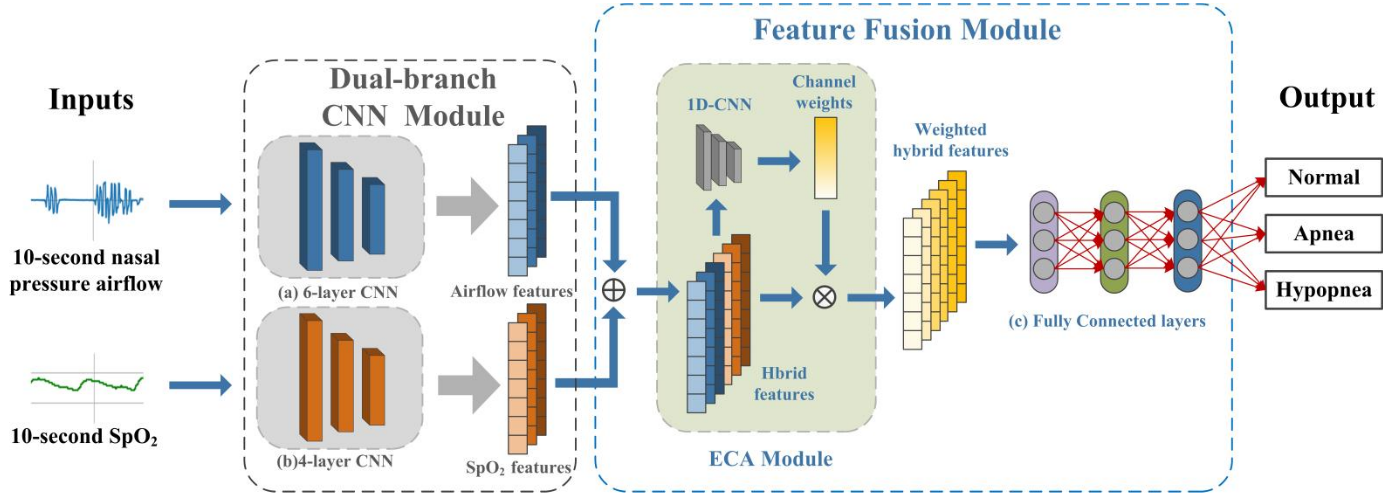


Figure 2: The overall architecture of bimodal feature fusion CNN. It mainly consists of two modules: a dual-branch CNN module and a feature fusion module.

- Results:

Comprehensive diagnostic performance of feature fusion CNN VS 1-D CNN, Mr-ResNet, LSTM-CNN, SVM and KNN

Model	Acc(%)	Sen(%)	Pre(%)	Spec(%)	F1-score
1-D CNN[14]	94.99	88.82	90.51	96.05	89.54
Mr-ResNet[24]	94.30	85.76	90.46	95.21	87.38
LSTM-CNN[23]	95.04	89.31	90.35	96.17	89.74
KNN	93.54	85.37	87.72	94.84	86.3
SVM[1]	93.67	83.47	89.79	94.60	85.31
6-layer CNN (this paper)	94.92	88.0	90.87	95.9	89.15
Feature-fusion CNN(this paper)	**95.91**	**90.59**	**92.39**	**96.76**	**91.38**

Nightmare

Nightmare (1781) by Henry Fuseli

Epileptic seizure detection

- Developing methods for automatic detection the abnormal patterns from EEG signals to diagnose epileptic seizure and also for prediction of impending seizure for early warning the patients

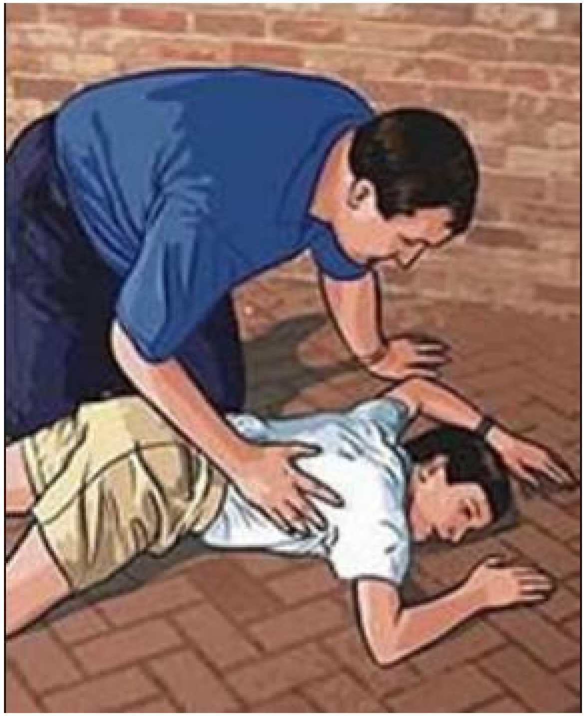
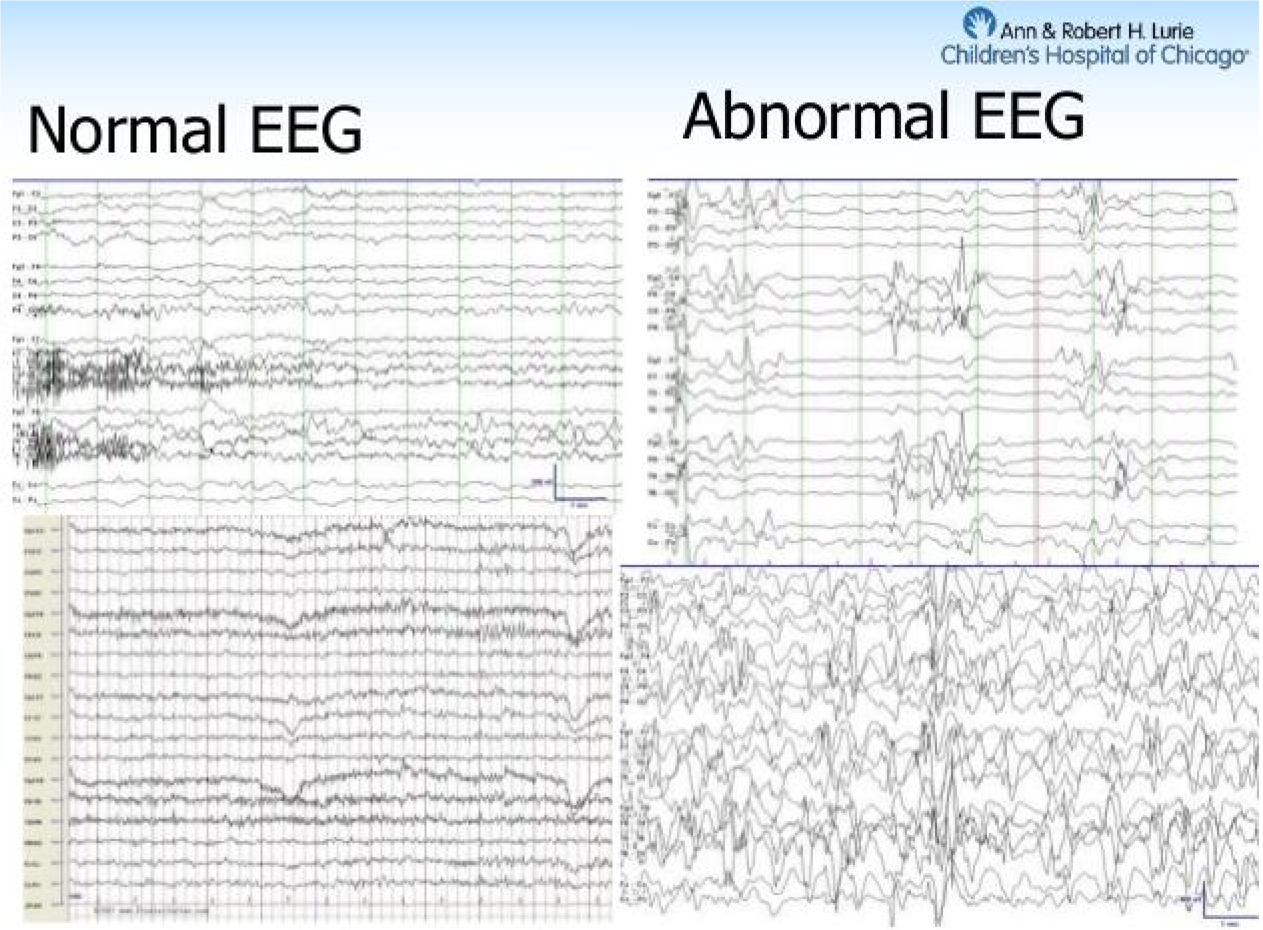


Fig.5: Images of epileptic patients during seizure activity

EXAMPLE OF NORMAL AND ABNORMAL EEG SIGNALS

- ❑ Normal EEG signals from a healthy subject
- ❑ Abnormal EEG from an epileptic patient during seizure

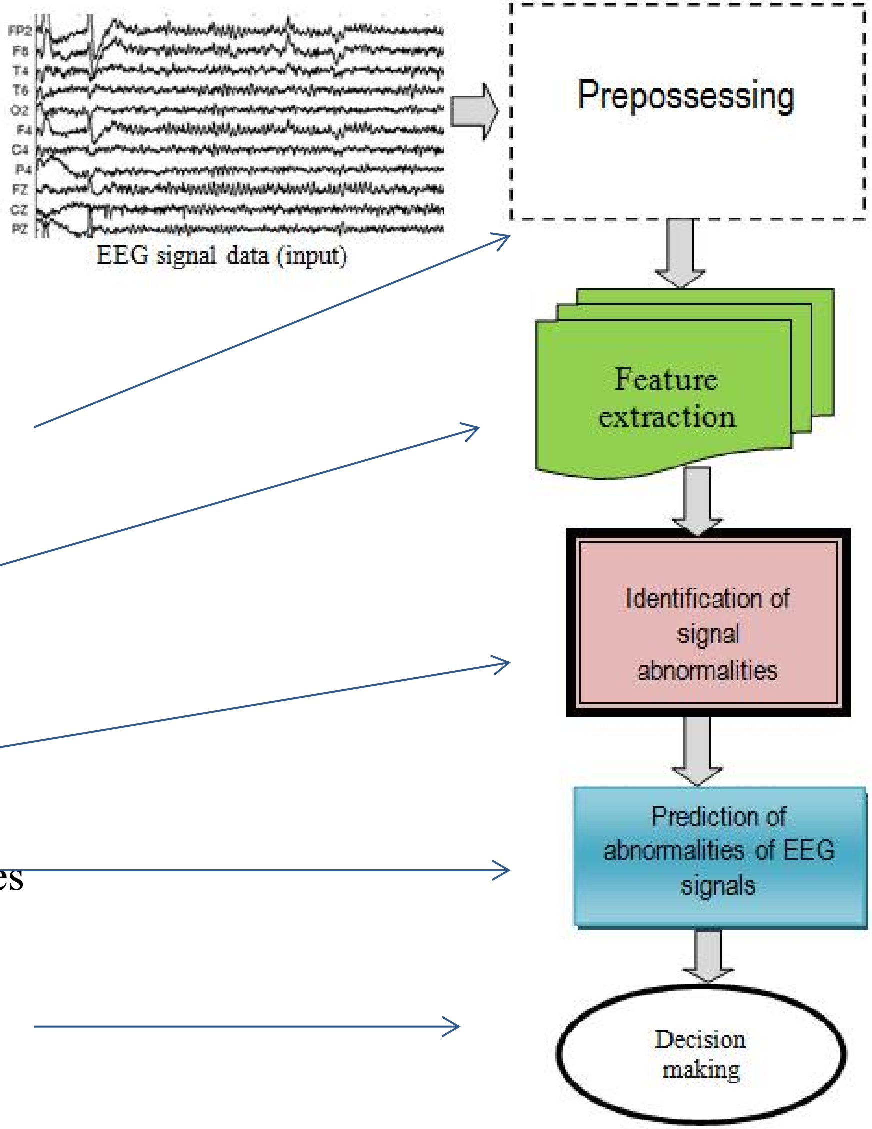


An example of normal EEG and abnormal EEG

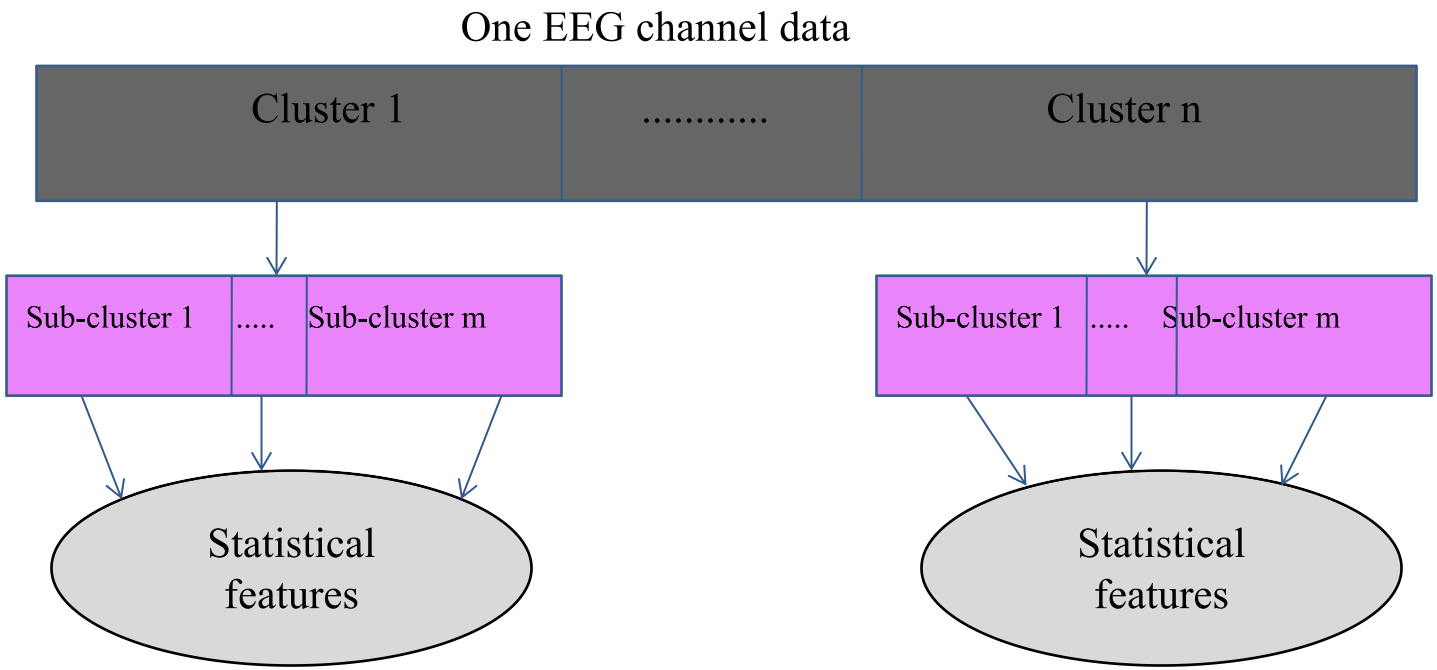
GENERAL FRAMEWORK FOR EARLY WARMING BASED ON EEG SIGNALS

This diagram shows a general diagram of EEG signal classification and also predicting approaching neurological problems from EEG data.
EEG signal analysis

- ❑ EEG signal prepossessing: remove noise/artifacts and windowing
- ❑ Feature extraction using appropriate technique
- ❑ Signal category identification/classification
- ❑ Prediction signal abnormalities for future warning
- ❑ Making decision based on the outcomes



PROPOSED CLUSTERING METHOD FOR FEATURE EXTRACTION



Clustering technique diagram for obtaining different clusters, sub-clusters and statistical features.

STATISTICAL FEATURE EXTRACTION

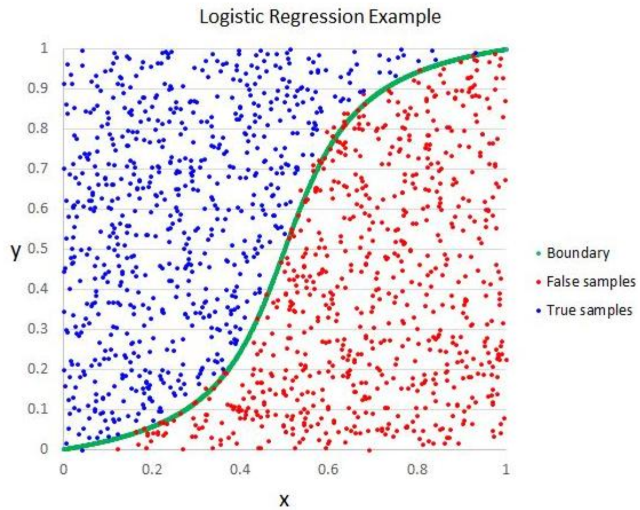
The following nine statistical features were extracted from each sub-cluster of each EEG channel data as the valuable parameters for the representation of the characteristics of the original EEG signals.

- *Minimum* (X_{Min})
- *Maximum* (X_{Max})
- *Mean* (X_{Mean})
- *Median* (X_{Me})
- *Mode* (X_{Mo})
- *First quartile* (X_{Q1})
- *Third quartile* (X_{Q3})
- *Inter-quartile range* (X_{IQR})
- *Standard deviation* (X_{SD}).

CLASSIFICATION: WHAT AND WHY

The classification *stage* involves the use of the classifier to determine the particular class of a signal based on its extracted features.

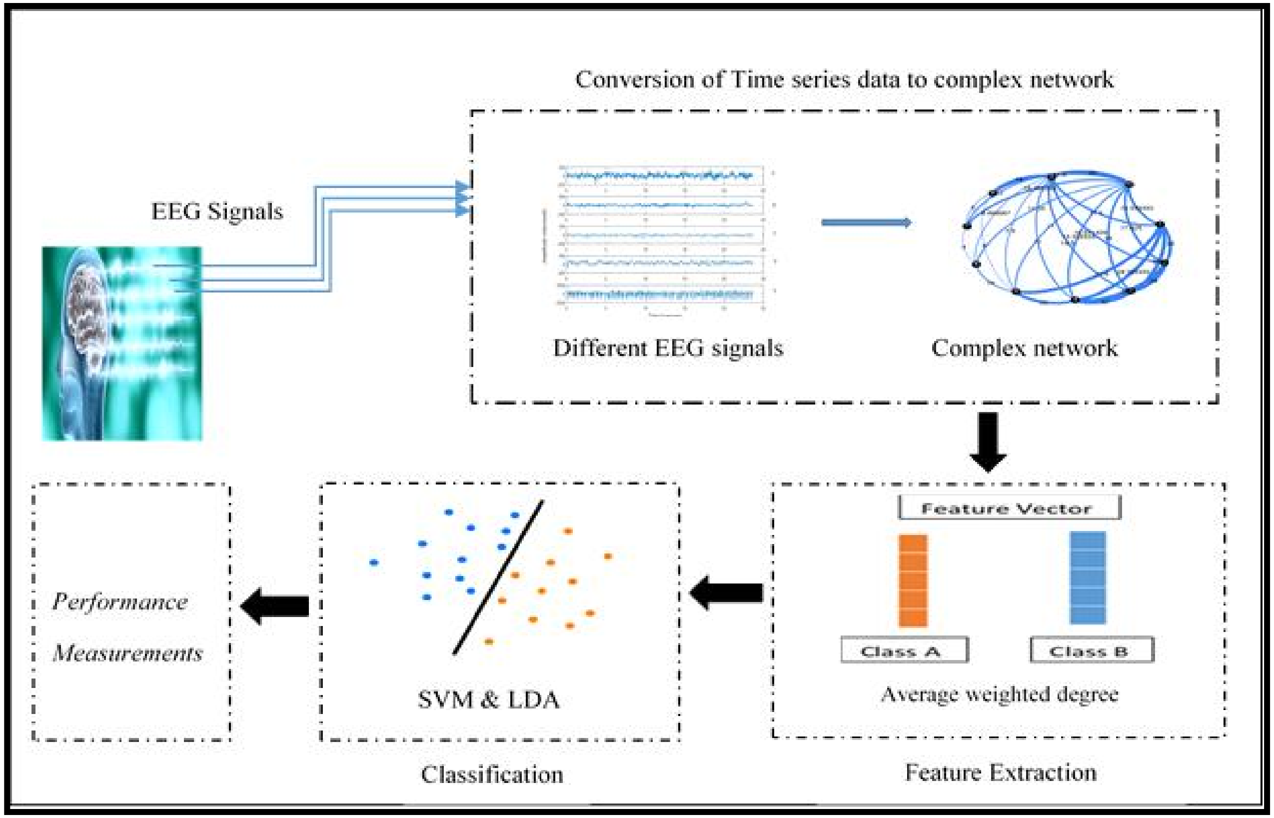
Feature set (input)

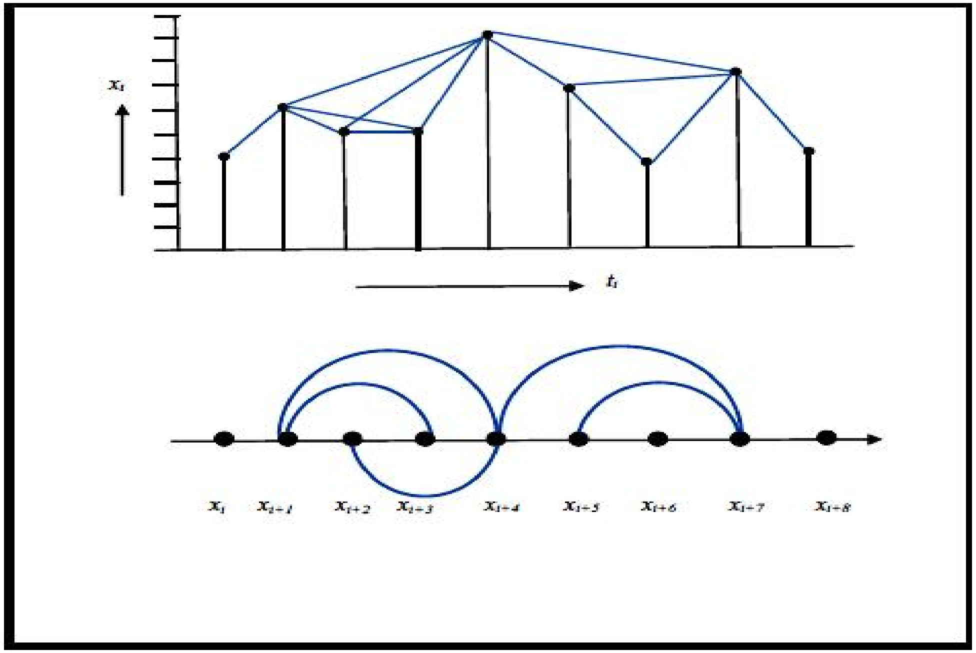


An example of classification

- **based on the selected signal features, a classifier determine to which class the signal belongs.**

Weighted Visibility Network





Visibility Graph

$$n_j < n_i + (n_k - n_i)\frac{t_j - t_i}{t_k - t_i}, k > j > i \quad (1)$$

$$w_{ij} = \frac{n_j - n_i}{t_j - t_i}, j > i \quad (2)$$

In this figure "x" represents the data sample points or voltage and "t" represents time value

Weighted Complex Network Of EEG data

- The thickness of edges in both figure are according to the edge weight values.
- The below figures demonstrate that the seizure activity EEG complex network is having more edge links as compared to healthy person EEG complex network.
- Due to sudden fluctuation in epileptic seizure, the complex network of epileptic patient is showing higher edge weight values as compared to EEG complex network of healthy person.

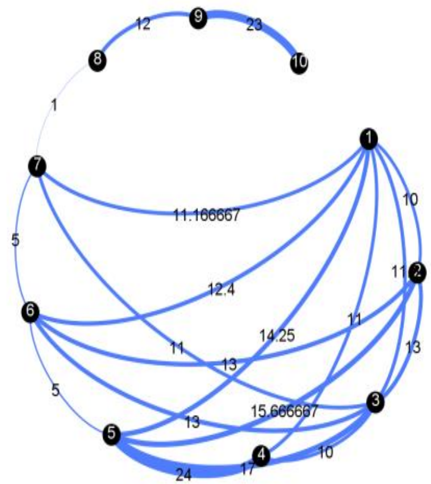


Fig. 2 Weighted complex network of healthy person

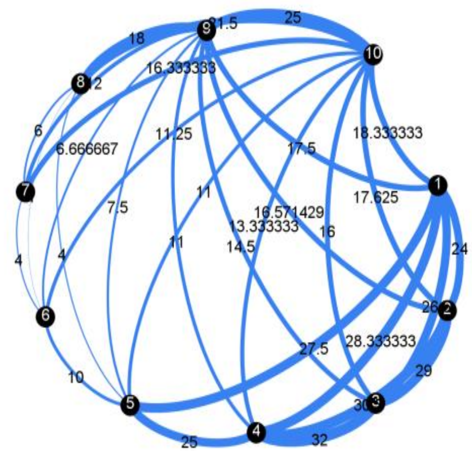
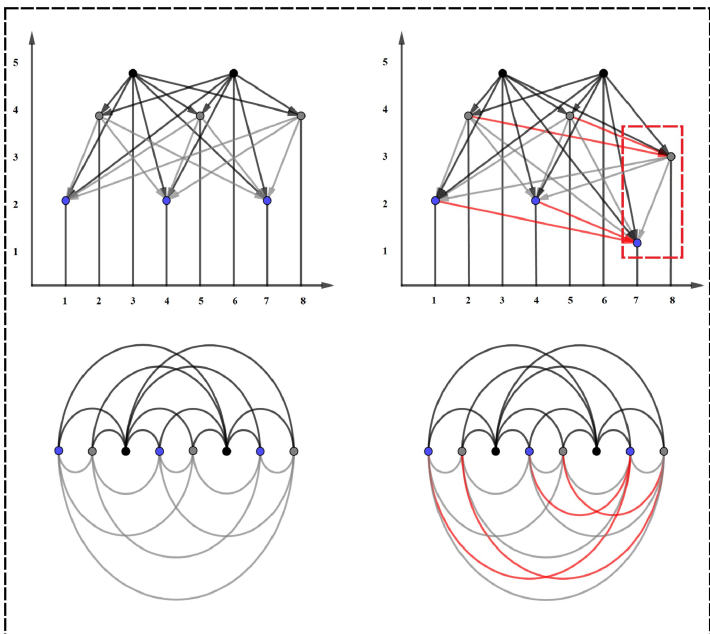


Fig. 3 Weighted complex network of Epileptic patient

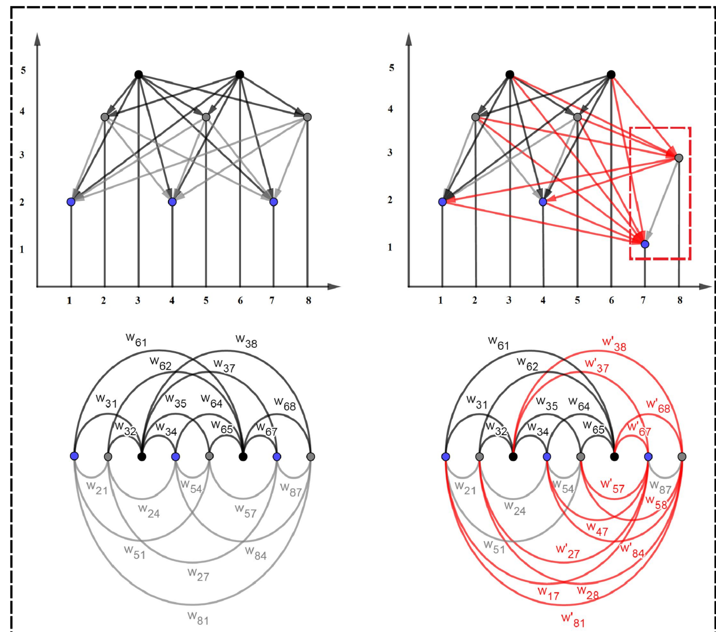
Overlook Graph approach

Jialin Wang, Shen Liang, Ye Wang, Yanchun Zhang, Dake He, etc,
A Weighted Overlook Graph Representation of EEG Data for Absence Epilepsy Detection", ICDM2020

OG



WOG



Time Series Representations/Transformations

- Discrete Fourier Transformation (DFT)
- Single Value Decomposition (SVD)
- Discrete Wavelet Transformation (DWT)
- Piecewise Aggregate Approximation (PAA)
- Adaptive Piecewise Constant Approximation (APCA)
- Symbolic Aggregate approXimation (SAX)
- Douglas-Peuker (DP) algorithm
- *EMD-IMF Mapping (Empirical Mode Decomposition - Intrinsic Mode Functions)*
- ….

精神病与认知障碍辅助诊断（Schizophrenia & Mild cognitive impairment）

Journals & Magazines > IEEE Transactions on Neural S... > Volume: 28 Issue: 11

A Computerized Method for Automatic Detection of Schizophrenia Using EEG Signals

Publisher: IEEE

Cite This

Siuly Siuly ; Smith K. Khare ; Varun Bajaj ; Hua Wang ; Yanchun Zhang

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Abstract | Authors | Figures | References | Citations | Keywords | Met

Feedback

Journals & Magazines > IEEE Transactions on Neural S... > Volume: 28 Issue: 9

A New Framework for Automatic Detection of Patients With Mild Cognitive Impairment Using Resting-State EEG Signals

Publisher: IEEE

Cite This

Siuly Siuly ; Ömer Faruk Alçin ; Enamul Kabir ; Abdulkadir Şengür ; Hua Wang ; Yanchun Zhang

Sign In or Purchase

Feedback

Schizophrenia (精神分裂症)

S Siuly, SK Khare, V Bajaj, H Wang, Y Zhang, **A Computerized Method for Automatic Detection of Schizophrenia Using EEG Signals**, *IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2020.*

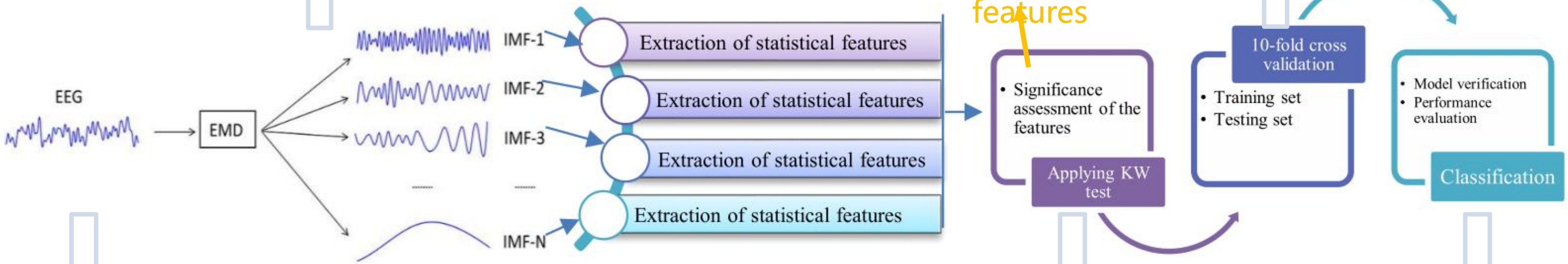
Automatic Detection of Schizophrenia

EMD: Empirical Mode Decomposition（经验模态分解)
IMF: Intrinsic Mode Functions（内涵模态分量)

EMD- IMF mapping

4 types of classifiers

22 features



EEG Pre-processing

KW validation

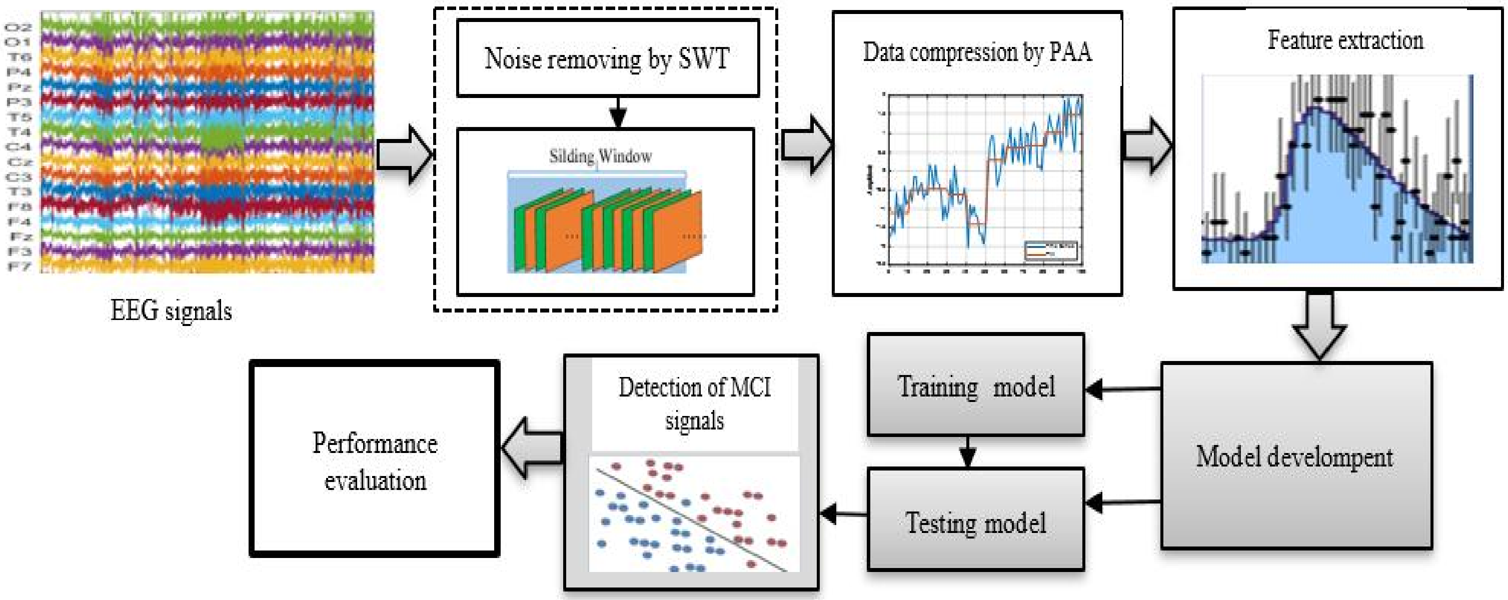
Classfied results

Mild Cognitive Impairment （认知障碍）

S Siuly, ÖF Alçin, E Kabir, A Şengür, H Wang, Y Zhang, F Whittaker, **A new framework for automatic detection of patients with mild cognitive impairment using resting-state EEG signals**, IEEE Transactions on Neural Systems and Rehabilitation Engineering 28, 2020

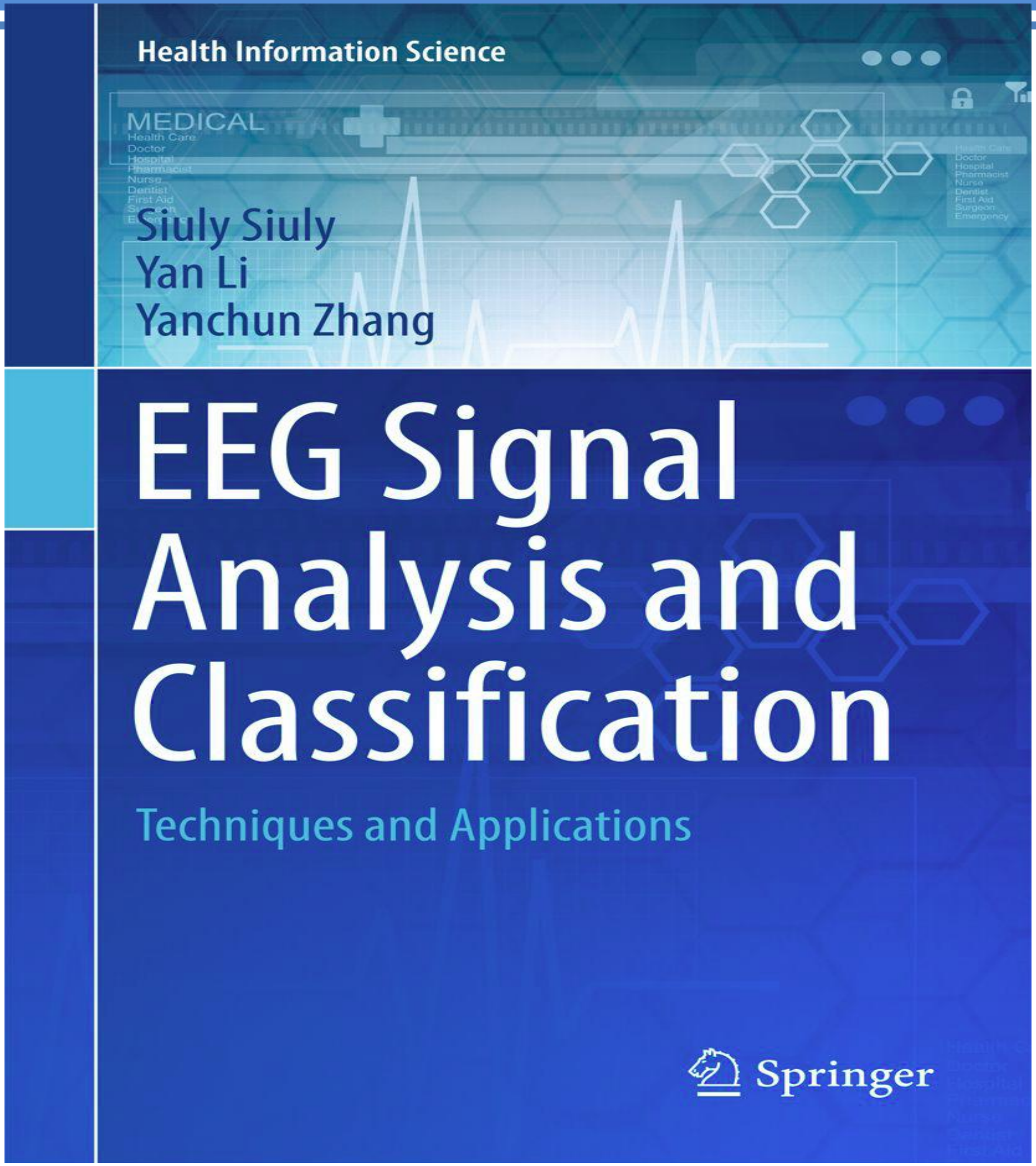
Mild cognitive impairment diagnosis

(1) noise removal; (2) segment data/making sliding window; (3) EEG data compression; (4) extract and aggregate suitable features; and (5) classification model for detection of MCI patients from healthy control subjects.



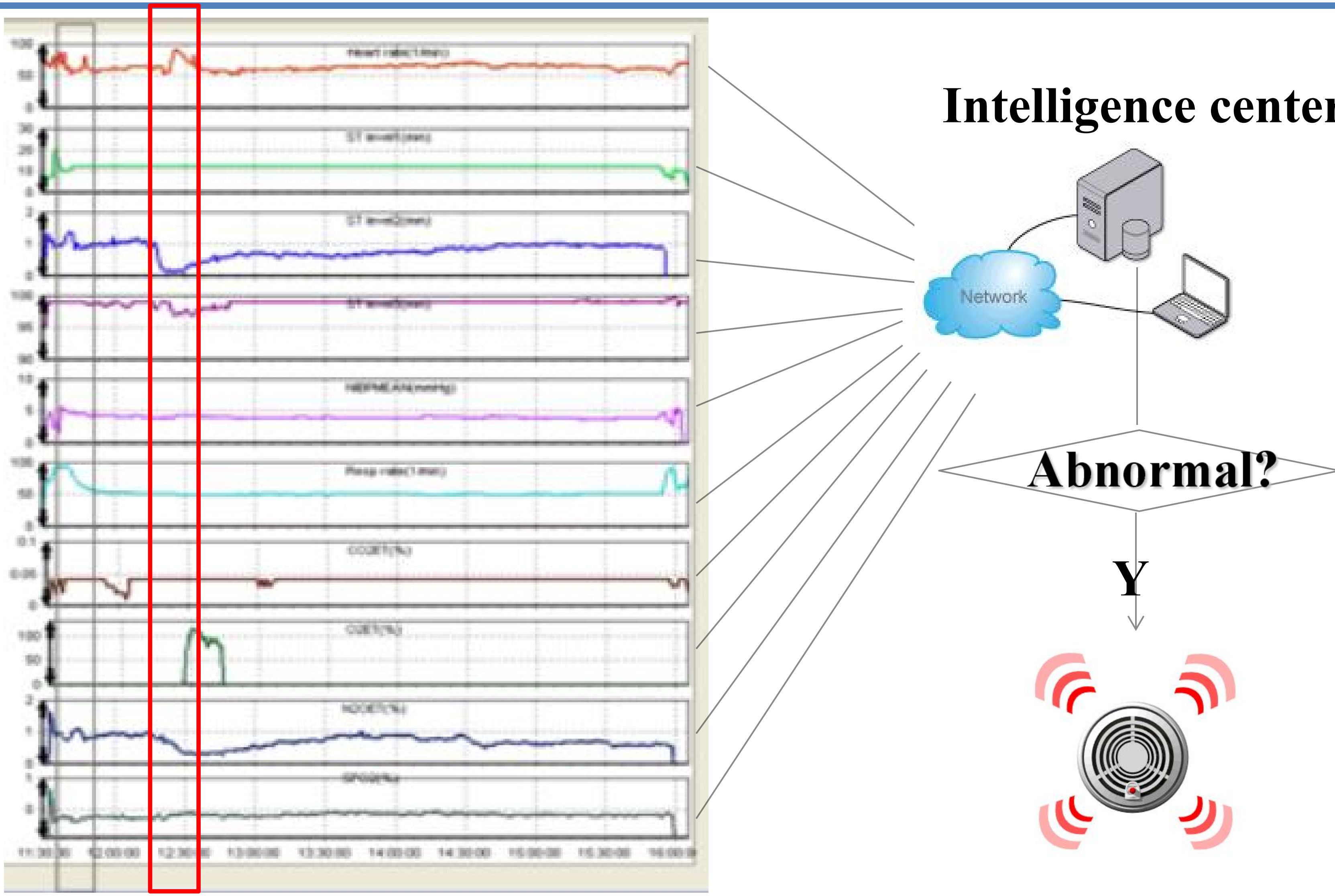
Proposed framework for automatic detection of MCI patients from EEG signal data

EEG Signal analysis and application



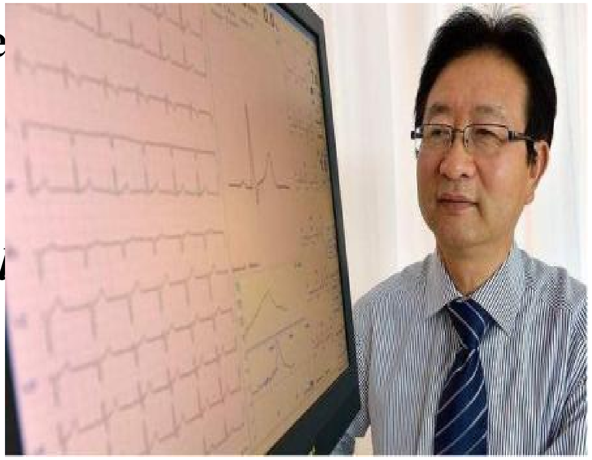
3. Abnormality detection and prediction for intensive care patients / surgery

Motivation/ Background


Intelligence center
Network
Abnormal?
Y

Media Release

- **The Australian, The Age, Canberra Time，Brisbane Time**
Sydney Morning Herold, 。。。。
- **A few seconds can save patients' lives,**
- **www.theage.com.au (The Age, March 11, 2013)**
- ***Surgery made safer with program that predicts patients' vital*** **Australian, March 26, 2013)**

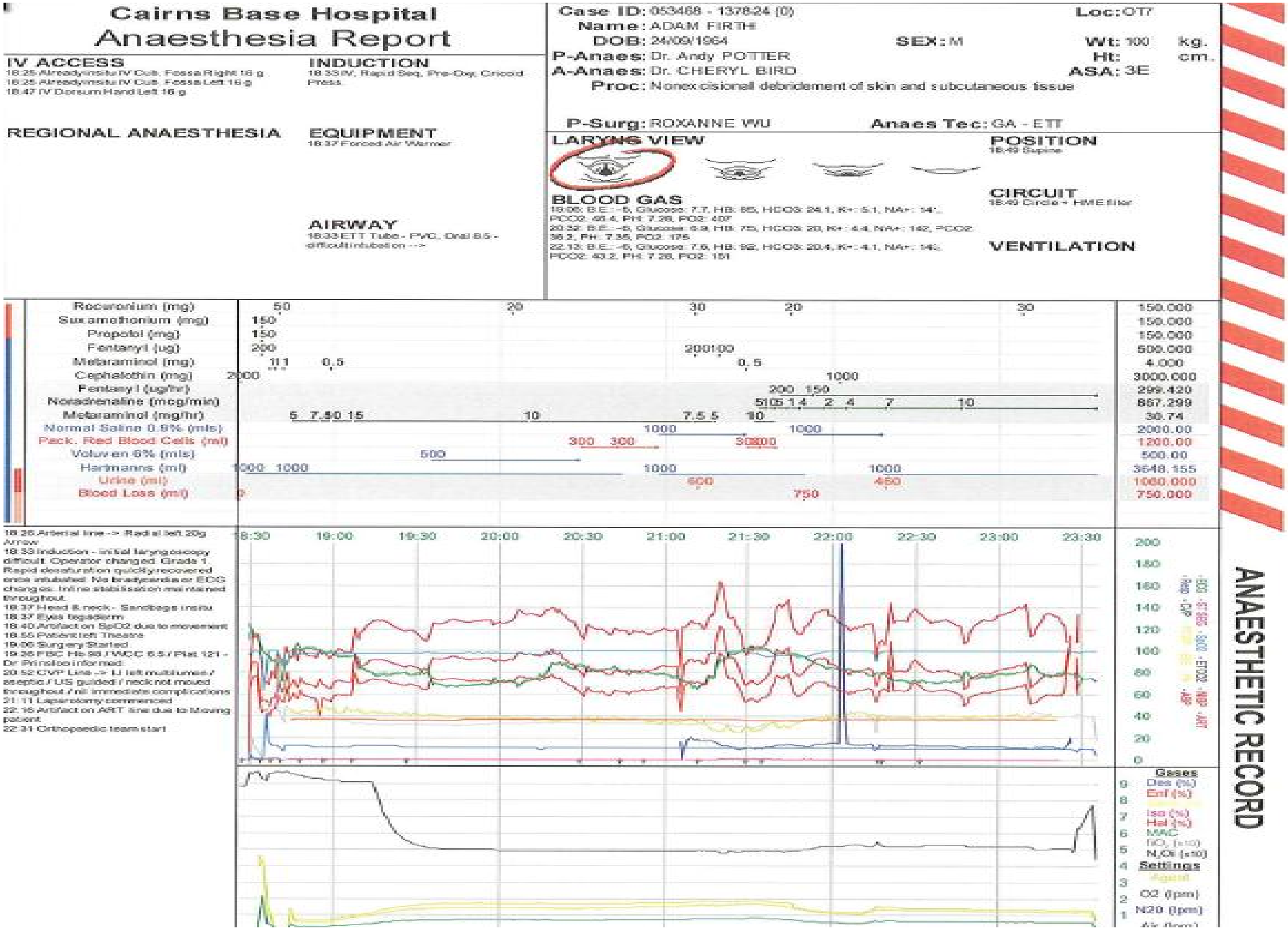


News in Chinese：
China Daily，ChinaNews，XinhuaNet，。。。

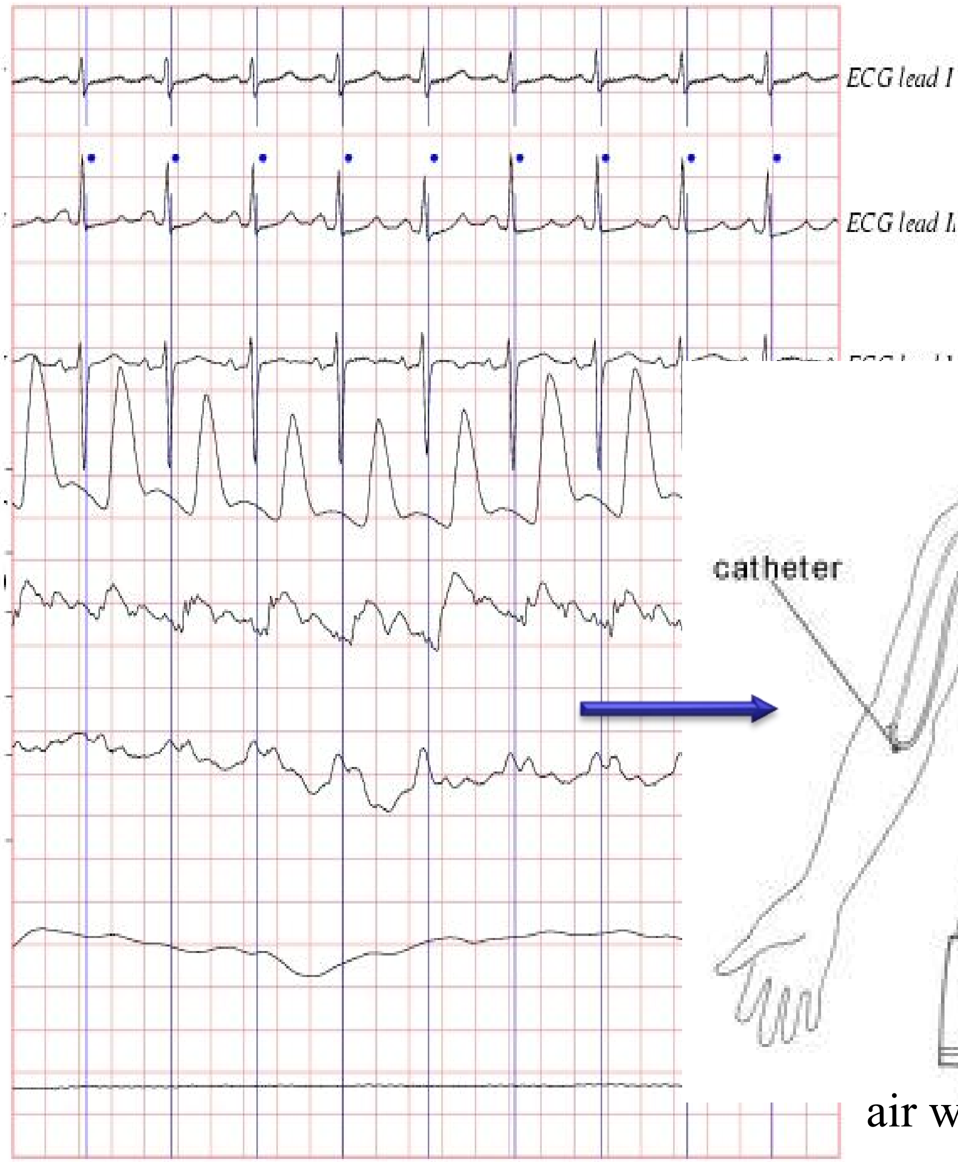
- ➢ **澳华裔教授研发计算机程序提前20秒预测患者病况-中新网**
- ➢ **华裔教授开发救命程序提前20秒预测患者病况**
- ➢ **華裔信息學家研發程式預測維生指數 - 星島聯網**

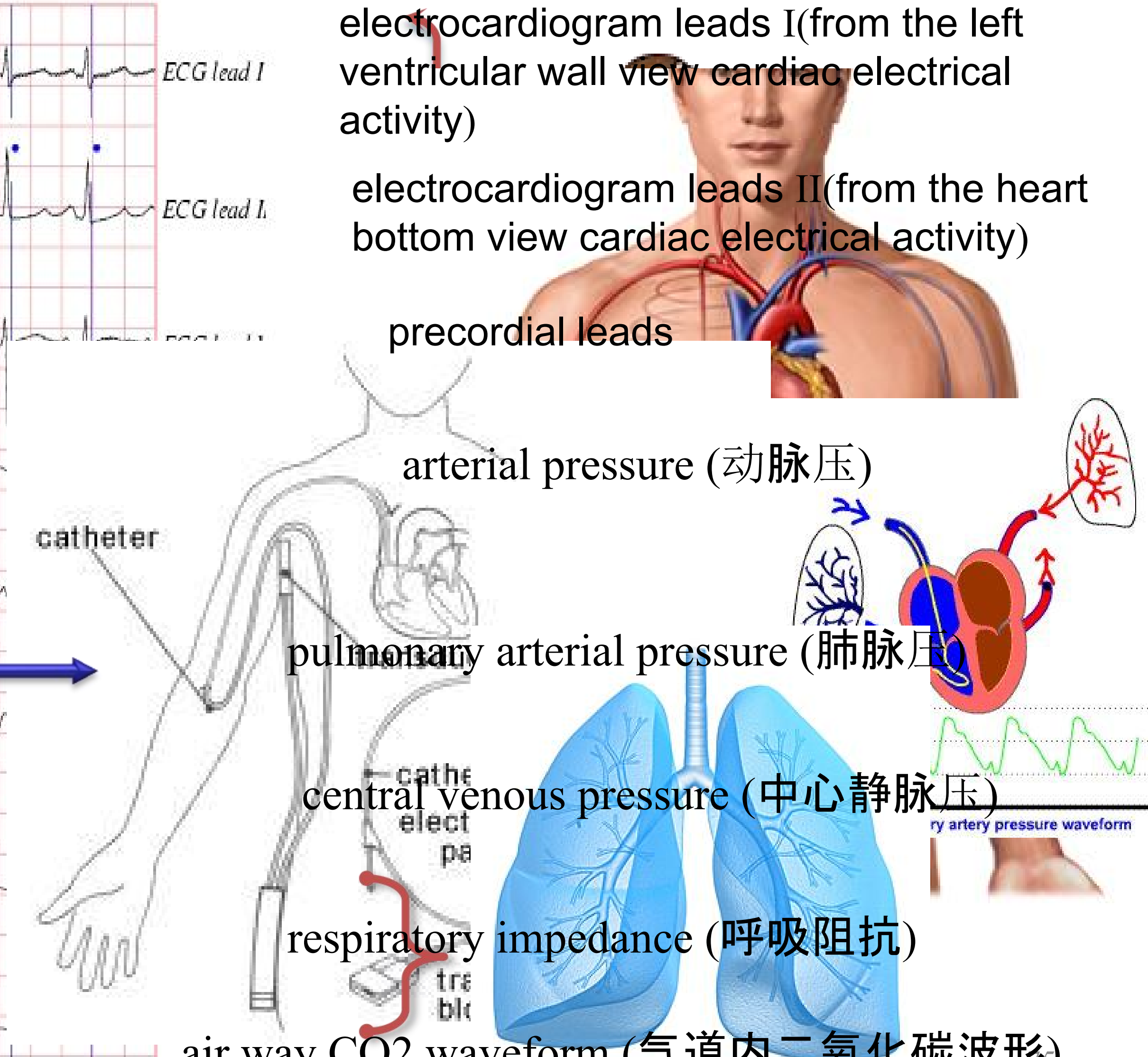
- ➢ **"One monitor/equipment will be enough for future surgery"**
- ➢ **"This could evolutionise emergence medicine"**

Automated Record Keeping(since 2001 in Cairns)



Background—physiologic data streams





electrocardiogram leads I(from the left ventricular wall view cardiac electrical activity)

electrocardiogram leads II(from the heart bottom view cardiac electrical activity)

precordial leads

arterial pressure (动脉压)

pulmonary arterial pressure (肺脉压)

central venous pressure (中心静脉压)

respiratory impedance (呼吸阻抗)

air way CO_2 waveform (气道内二氧化碳波形)

Background—Abnormality Detection from Physiological Data Streams

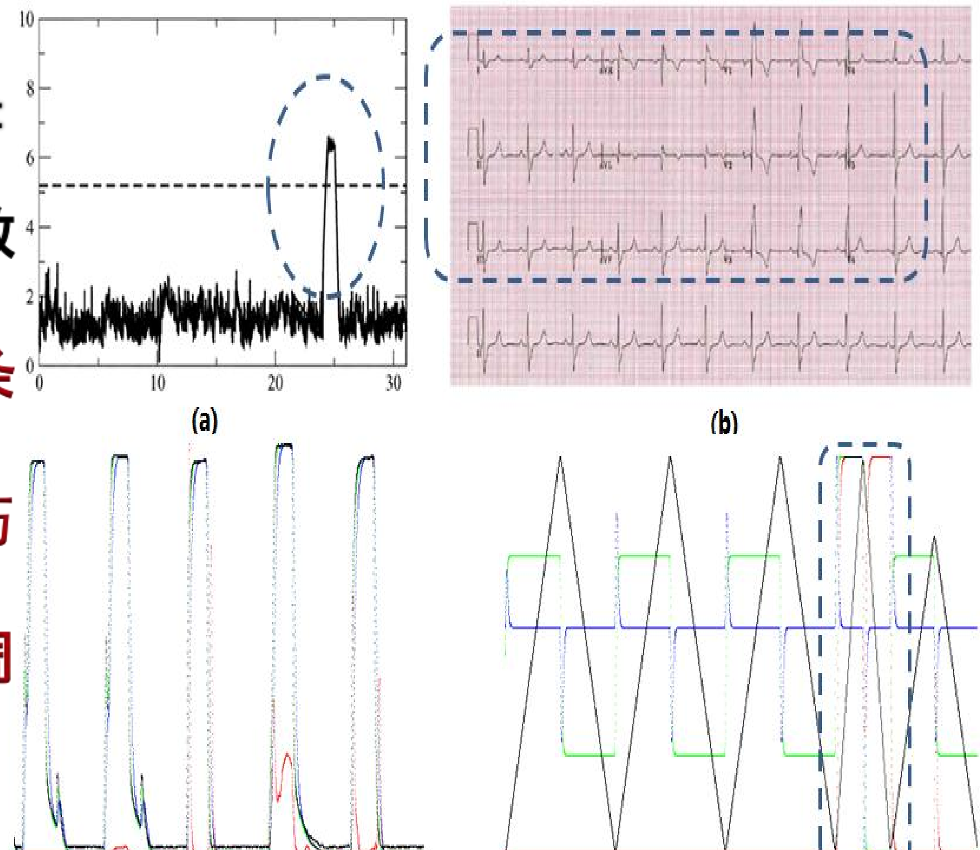
Generally, there are four kinds of abnormalities in physiological data streams:

a) Value Abnormalities (噪音,数据丢失,采样干扰等)

b) Correlated Abnormalities(多条曲线相关变化识别不同的异常)

c) Pattern Abnormalities(对比历史值,周期模式变为非周期模式)

d) Frequency Abnormalities(周期长度变得异常)



For example 1, anomaly with multiple physiological data associations, it can identify different symptoms/diseases (b)

For example 2, with periodical/frequency anormallies, it can identify key diseases on heart and lung (c),(d)

The case of abnormal relationship during the physiological data

1. In general cases, the **heart rate and pulse** are consistent. But when the cardiac is arrhythmias such as Atrial Fibrillation, frequent premature beat, the pulse will be less than the heart rate**.**

2. The ratio of breathing frequency/pulse number is 1:4. If the ratio changes, human body is abnormal.

3. Drop of blood pressure + pulse quicken + shortness of breath + temperature drop → danger

Warning for abnormal health in ICU

- Collect as many as seven different data streams from the intensive care unit / surgery room.
- Compress huge raw data.
- Propose a data stream mining algorithms
- Warn abnormal health associated with some diseases / syptoms.
- Develop a medical diagnosis system.
- Analyze the risk of patients, and predict disease/abnormality so as to save the lives of patients.

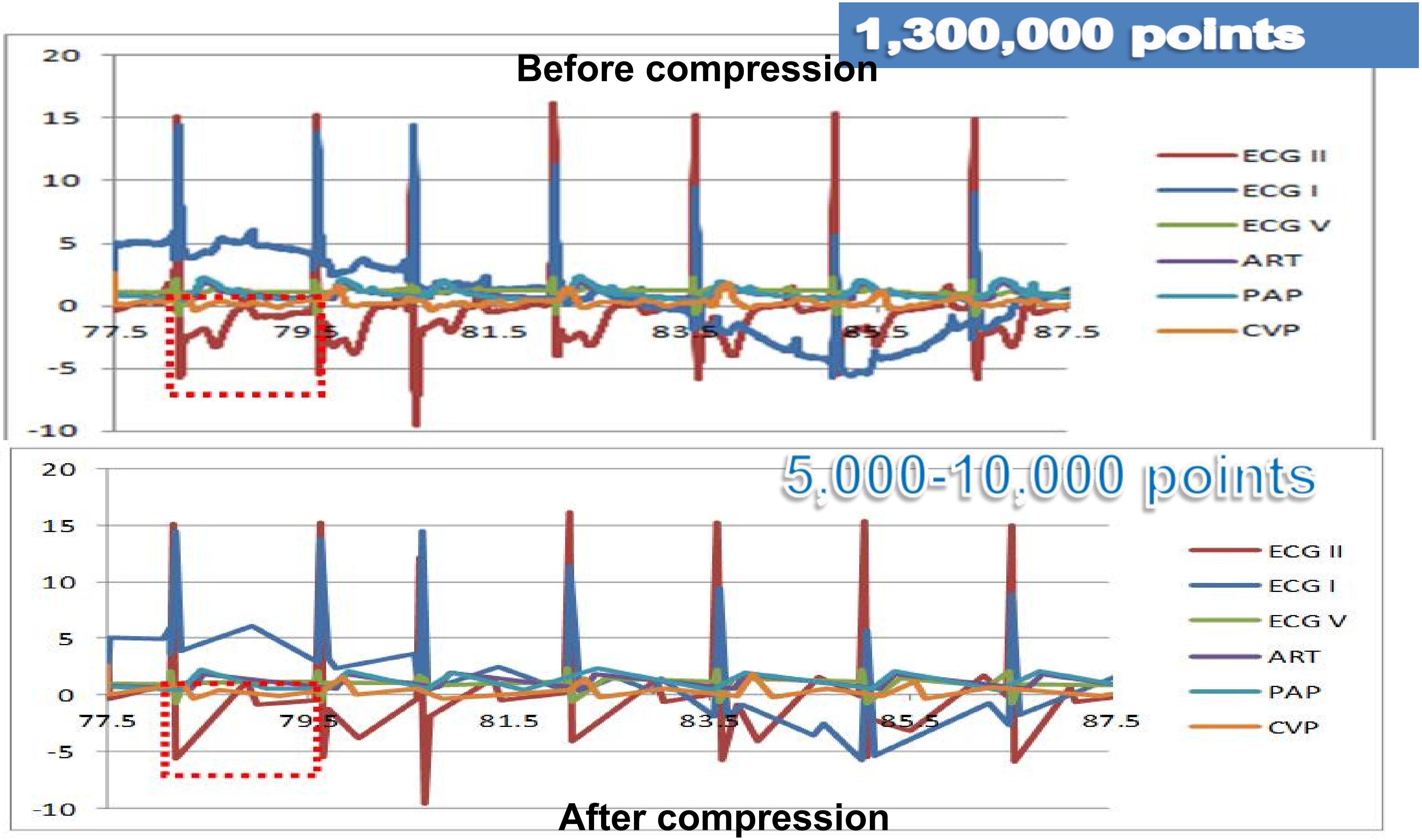
Discovering Periodical Patterns from Compressed Single Streams

Step 1: Compressing data by using Douglas-Peuker (DP) approach

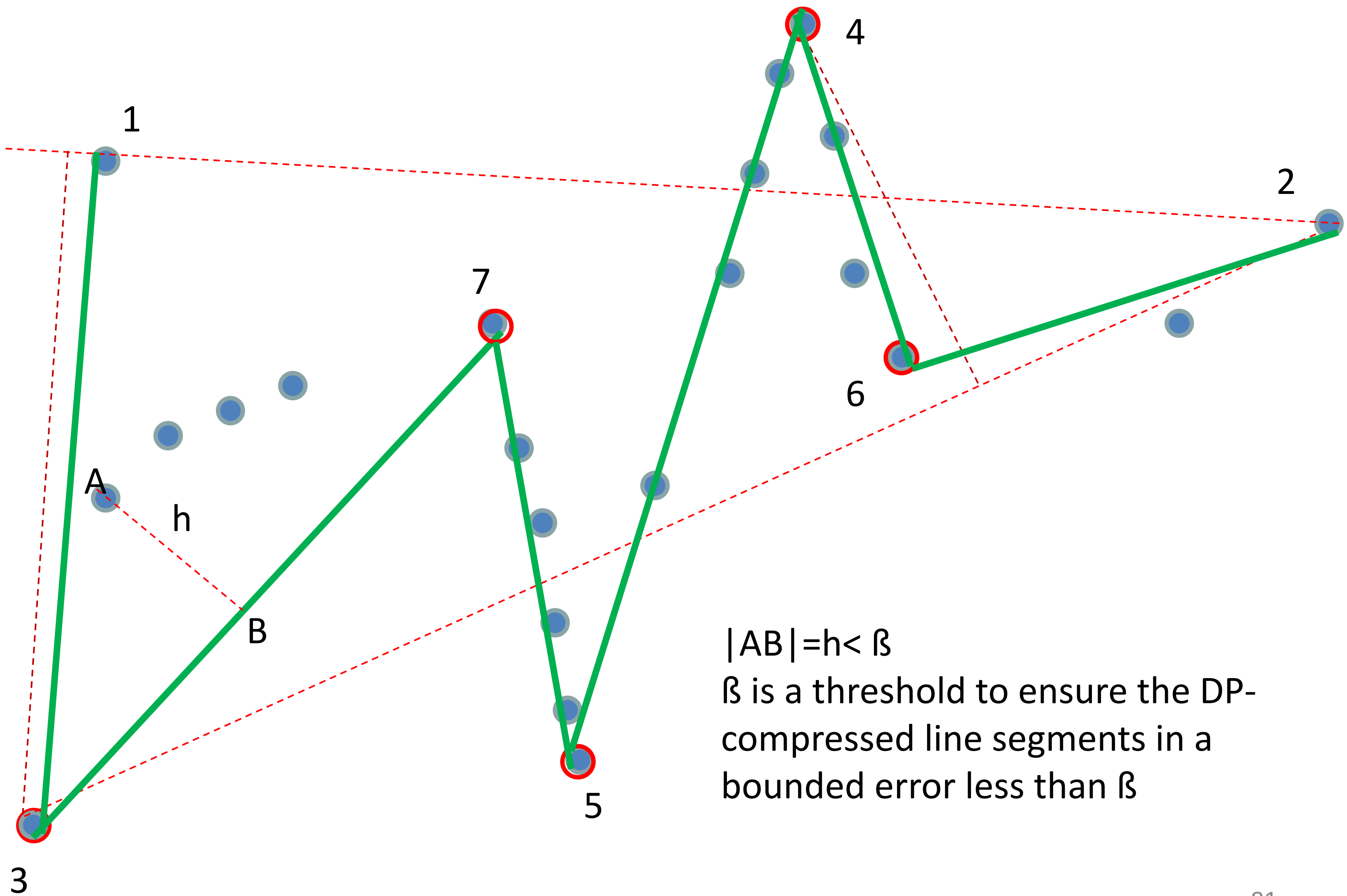
Step 2: Clustering critical points（CPOL）

Step 3: Analyzing the peak points

Step 1. Compression



DP compression (压缩)

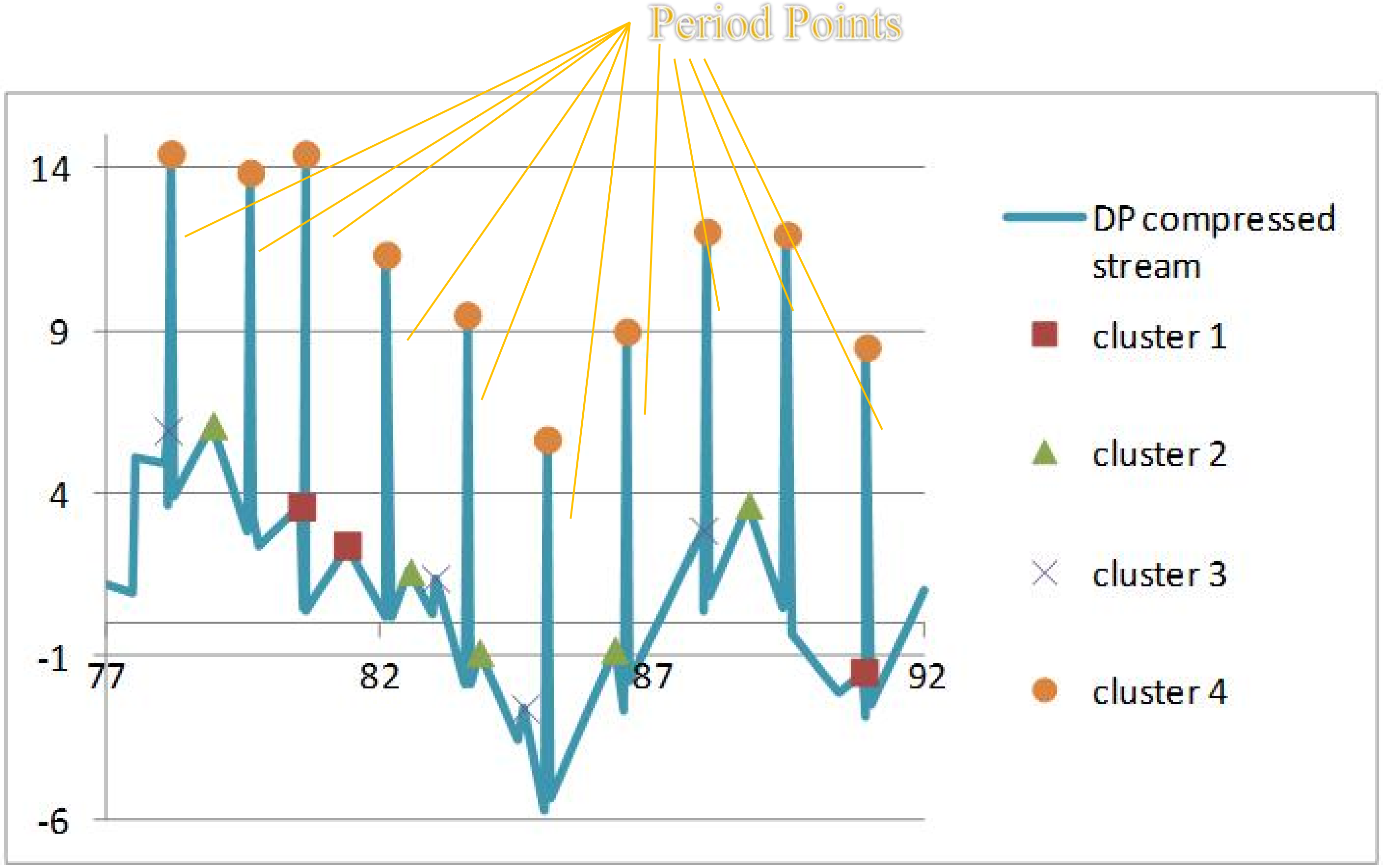


|AB|=h< ß

ß is a threshold to ensure the DP-compressed line segments in a bounded error less than ß

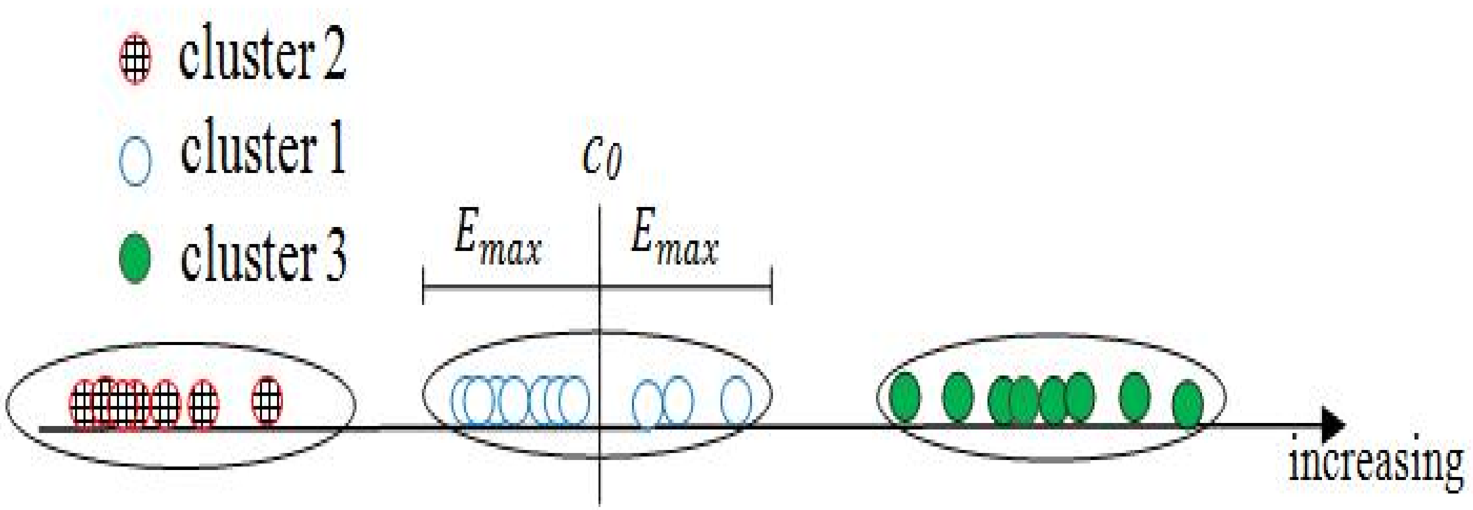
Get peak points: The DPPCSS Algorithm

Periodic feature extraction

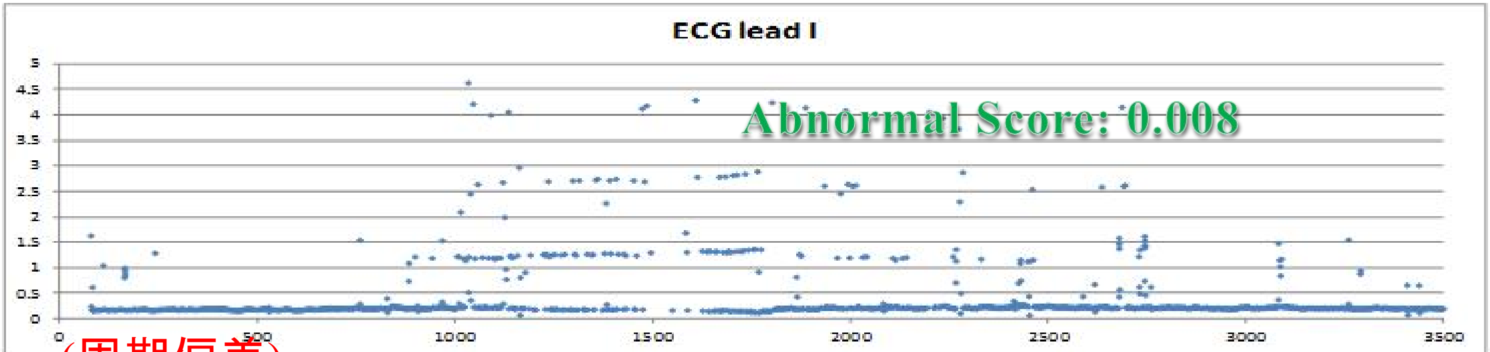


Step 2 : cluster data

- **Points are clustered based on their values, .**
- **C0 is cluster's center, all points around C0 belong to cluster 1**
- **Other points are in cluster 2 and cluster 3**



Anomaly analysis: The MAP3D Algorithm – computing abnormal scores

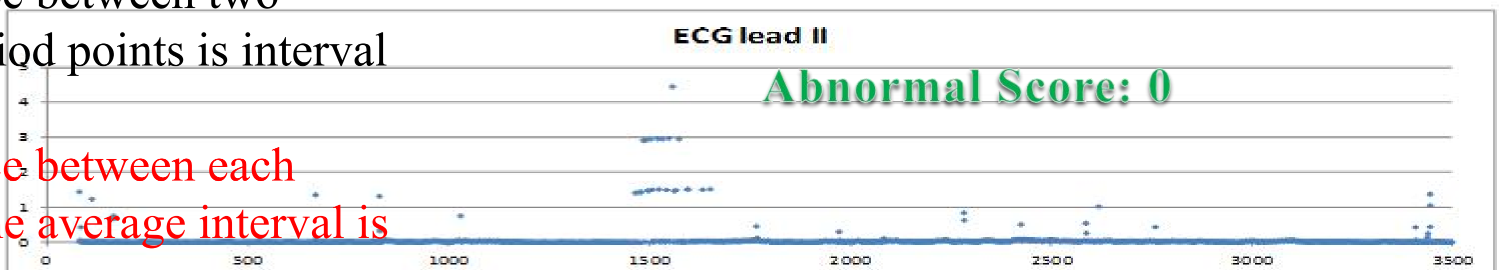


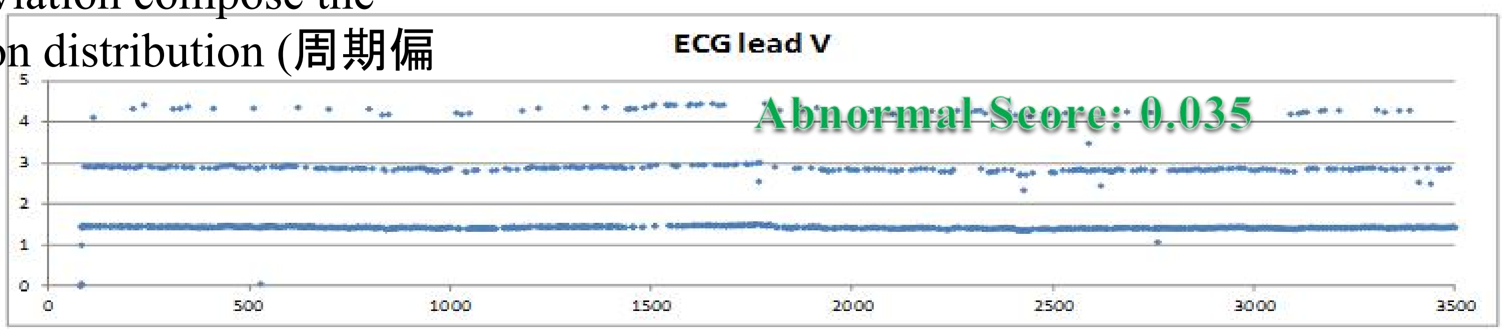
Period Deviation (周期偏差):

•The difference between two sequential period points is interval (间隔)

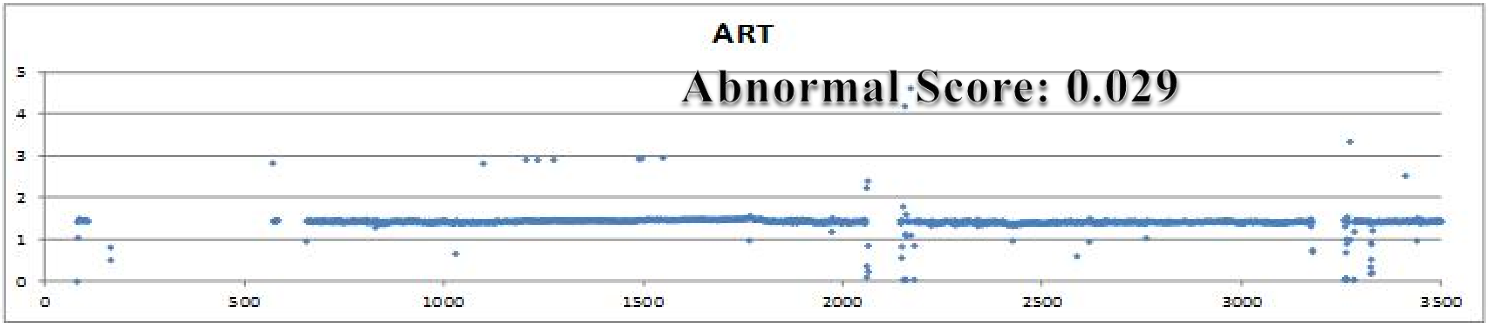
•The difference between each interval and the average interval is period deviation

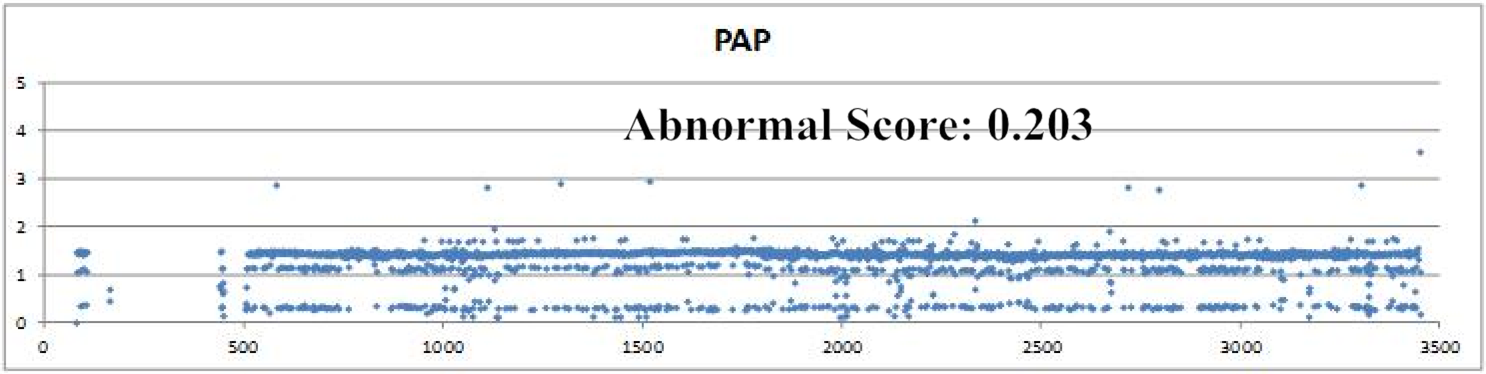
•All period deviation compose the period deviation distribution (周期偏差分布)

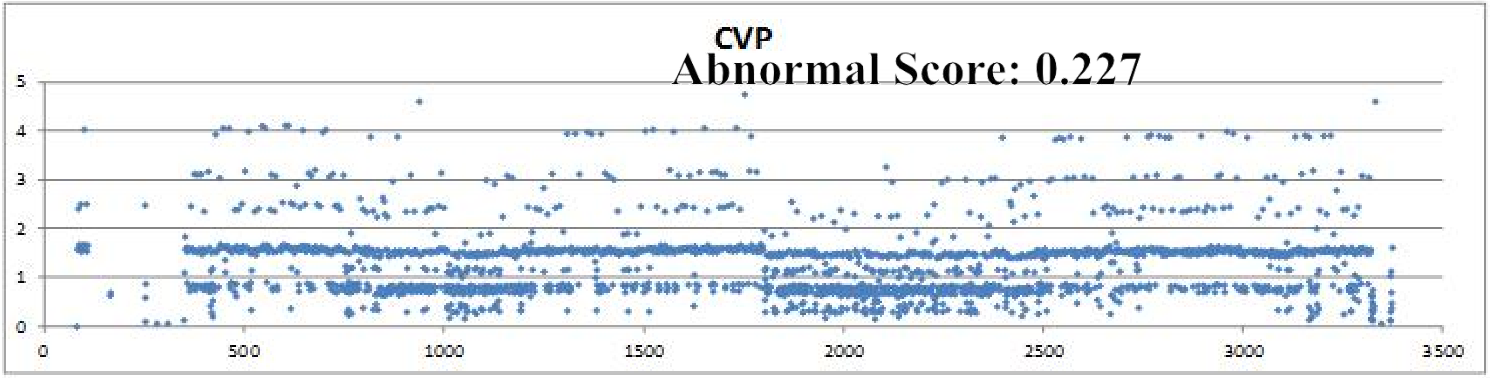




Period Deviation Distributions (cont.)







Period Deviation Distributions

- Doctor’s Comments in Natural Language:
  - sentence 1: “Cannon waves in CVP due to A-V asynchrony with CHB.“
  - sentence 2: “Retrograde cannon wave effect in pulmonary arterial trace.“ 逆向炮波
  - sentence 3: “Pulmonary hypertension. “ 肺动脉血压增高
- Translated to:
  - CVP and PAP (pulmonary arterial pressure) are abnormal

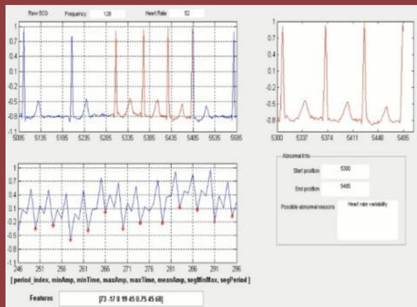
  中心静脉压 & 肺动脉压 异常

A “cannon wave” occurs when the right atrium contracts against a closed **tricuspid valve** causing a large pulsation to occur in the jugular venous pulsation. This occurs at times of electrical “AV dissociation”, the P wave on the ECG overlaps with the QRS complex and thus atrial systole occurs simultaneously with ventricular systole. This can result in significant stretch of the atrium causing ANP (Atrial Natriuretic Peptide) to be released causing polyuria.

面向重症和手术麻醉场景的心电异常监测

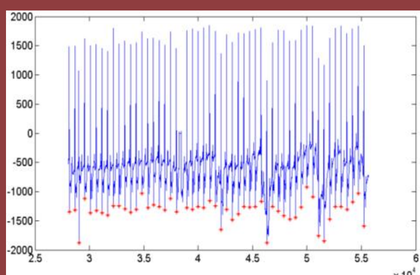
合作单位：复旦大学附属中山医院

技术路线1：周期性异常监测



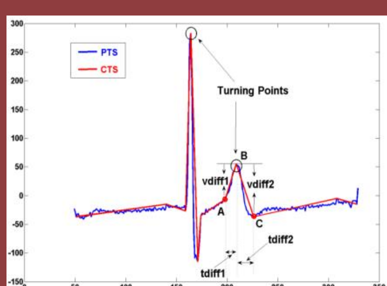
3. 周期性异常检测

在线搜索周期性紊乱的心拍，检测异常



2. 周期点识别

搜索关键的周期点，分析周期性



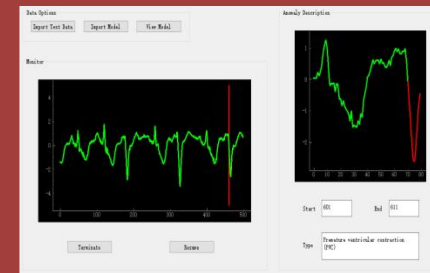
1. 数据压缩

自适应数据压缩，在保留关键语义的同时降低噪声、提高效率

技术路线2：波形异常监测

3. 波形异常检测

将实时监测数据与特征波形进行相似性匹配，搜索异常波形

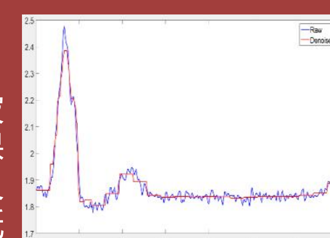


2. 特征波形搜索

搜索区分度高、医学可解释性好的特征波形

1. 数据降噪

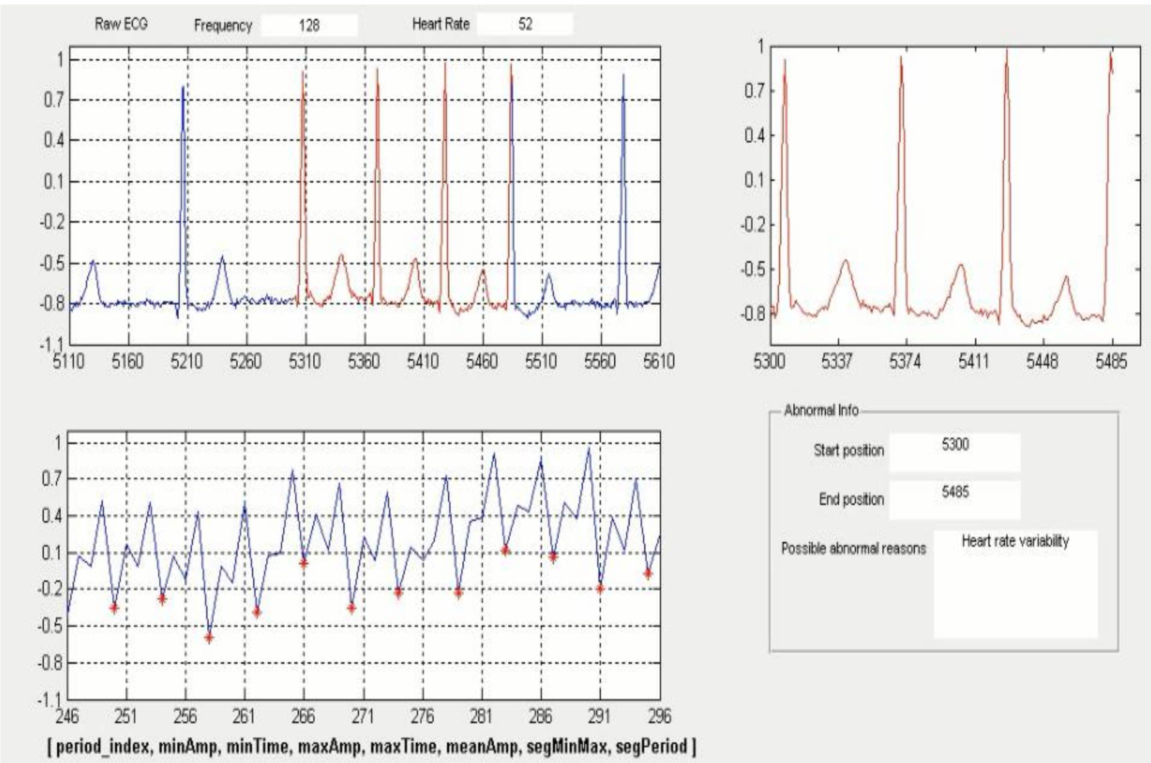
自适应小波降噪，在保留关键语义的同时降低噪声

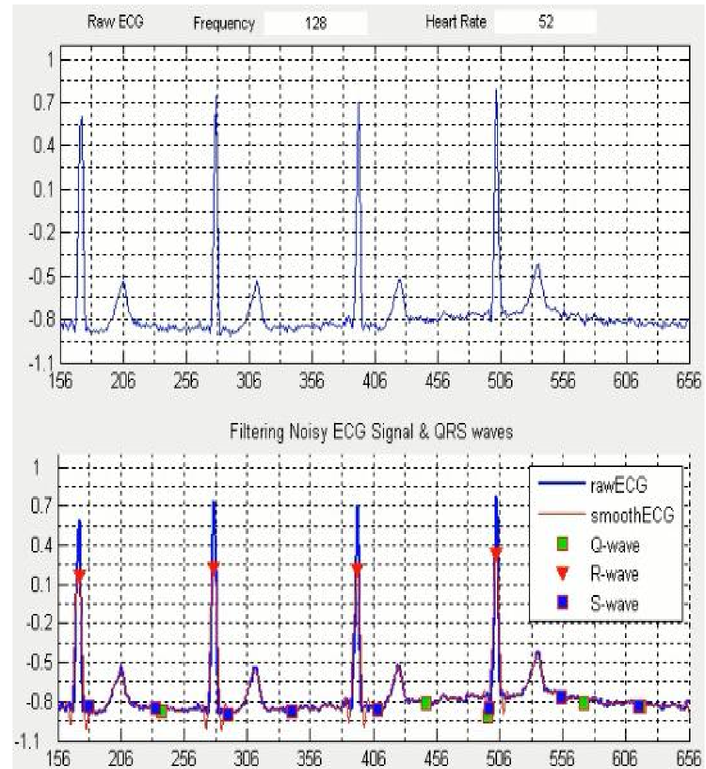


[1] Jiangang Ma, Le Sun, Hua Wang, Yanchun Zhang, Uwe Aickelin: Supervised Anomaly Detection in Uncertain Pseudoperiodic Data Streams. ACM Trans. Internet Techn. 16(1): 4:1-4:20 (2016)
[2] Jing Zhou, Shanfeng Zhu, Xiaodi Huang, Yanchun Zhang: Enhancing Time Series Clustering by Incorporating Multiple Distance Measures with Semi-Supervised Learning. J. Comput. Sci. Technol. 30(4): 859-873 (2015)
[3] Lexiang Ye, Eamonn J. Keogh: Time series shapelets: a novel technique that allows accurate, interpretable and fast classification. Data Min. Knowl. Discov. 22(1-2): 149-182 (2011)

心电监护原型系统：基于周期性分析

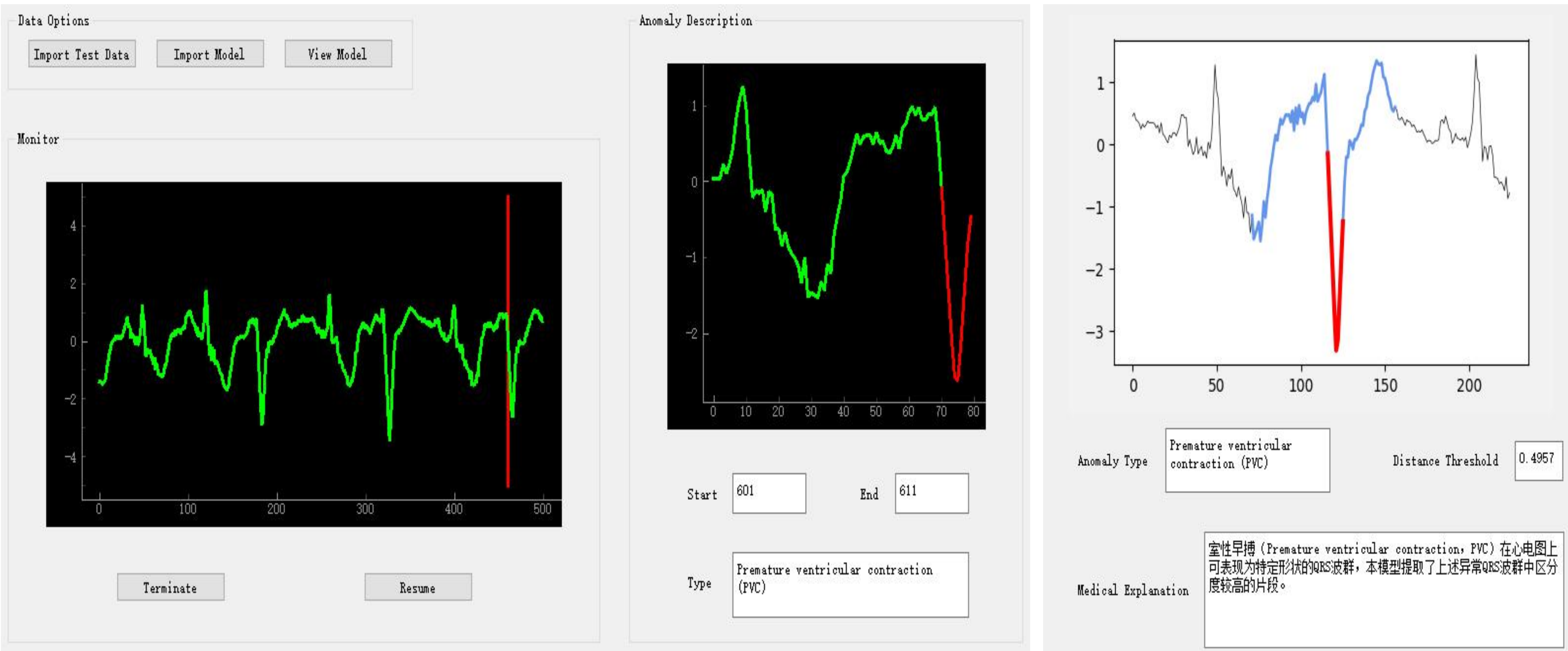
合作单位：复旦大学附属中山医院

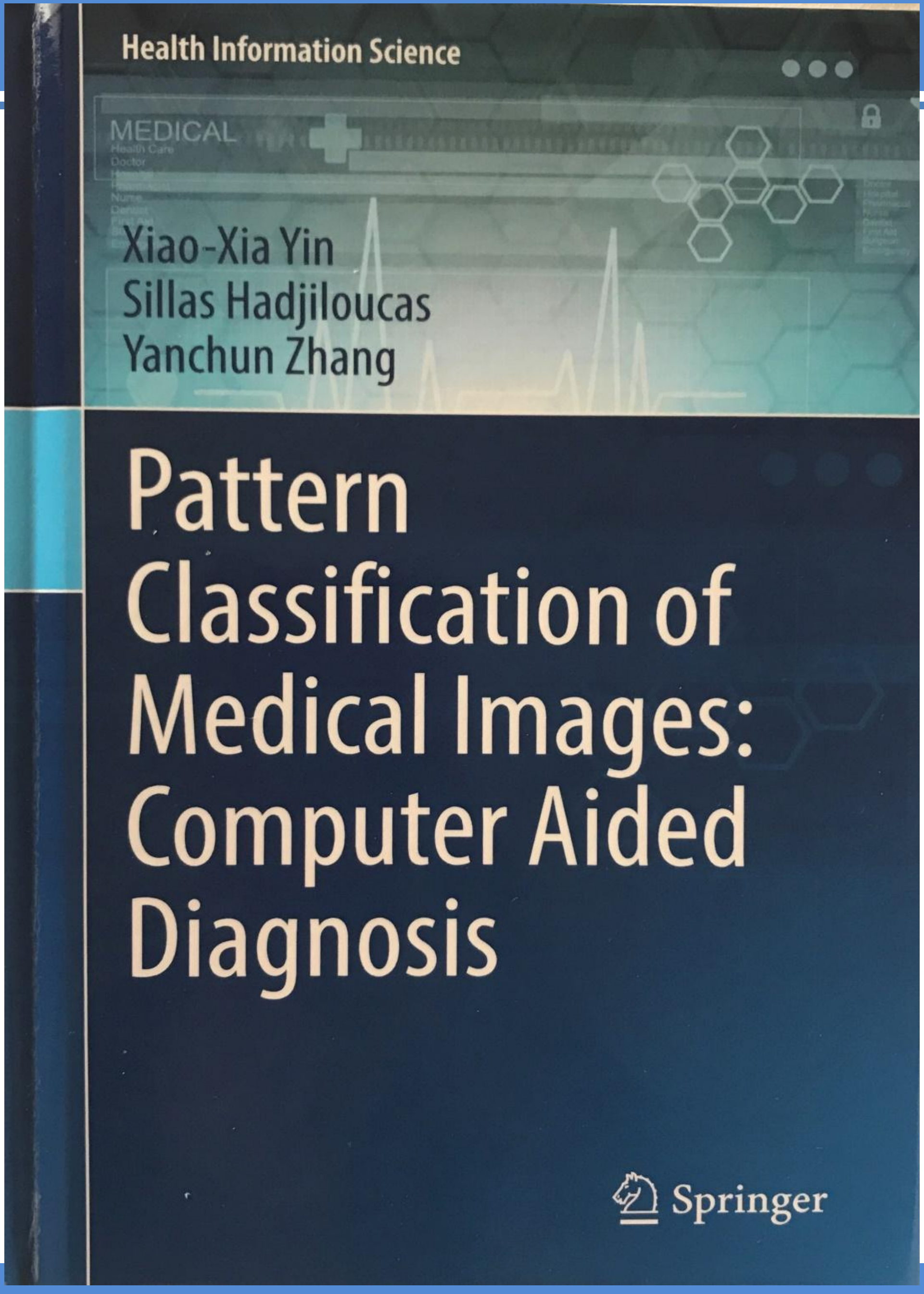




心电监护原型系统：基于特征波形搜索

合作单位：复旦大学附属中山医院




Health Information Science
MEDICAL
Xiao-Xia Yin
Sillas Hadjiloucas
Yanchun Zhang
Pattern Classification of Medical Images: Computer Aided Diagnosis
Springer

4. summary and prospect

Summary：

Medical big data

Data acquisition, information fusion, and correlation analysis

Accurate prediction, early warning, decision support, health guidance based on data analysis

Product/software to be applied to clinical, household, and community

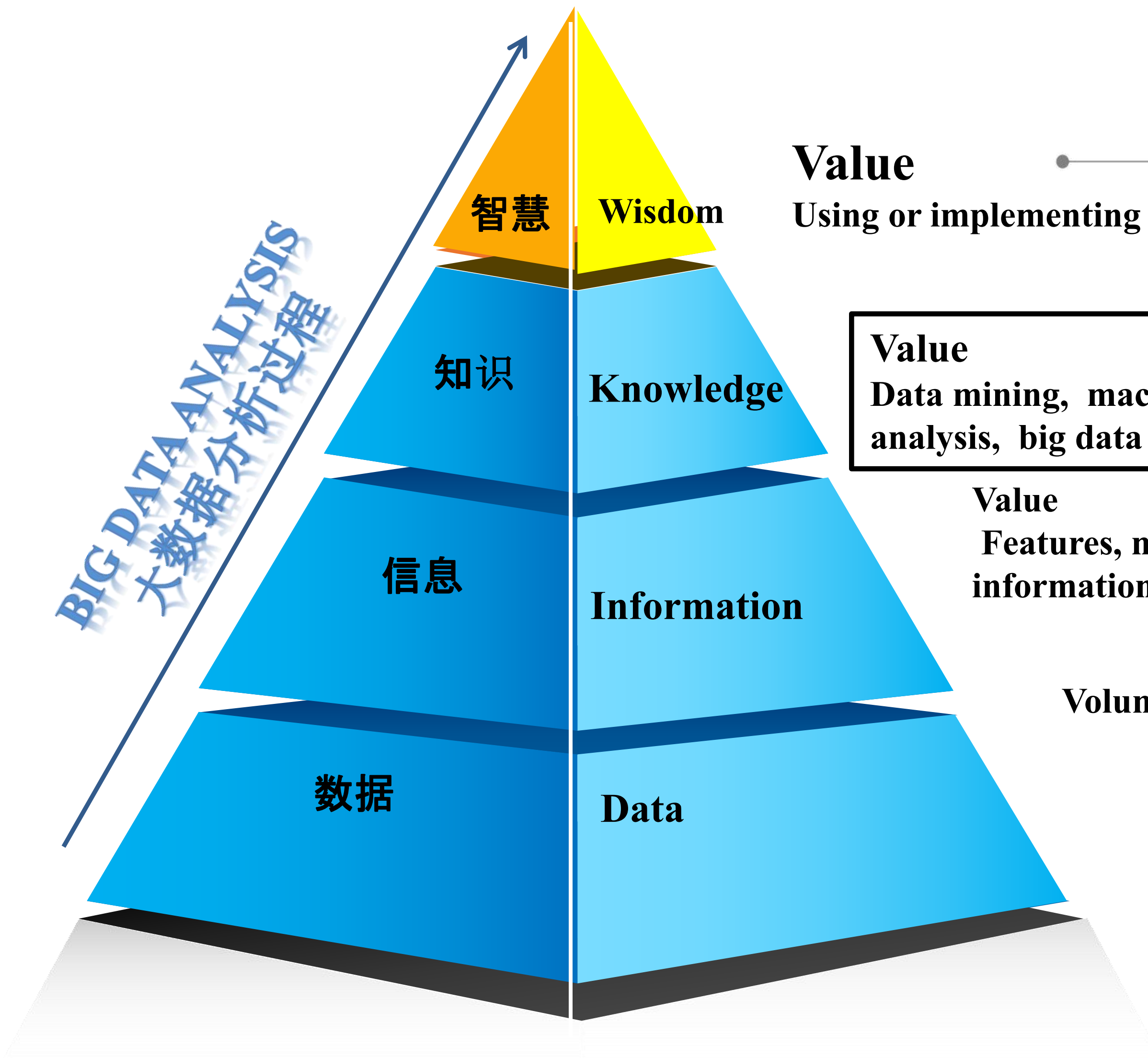
Other prospects

Health factors, Personalized medicine, Accurate medicine

Environment and health, further correlation analysis

Close cooperation with experts and scholars in the field of medical/health areas！！

Data-information-Knowledge-Wisdom



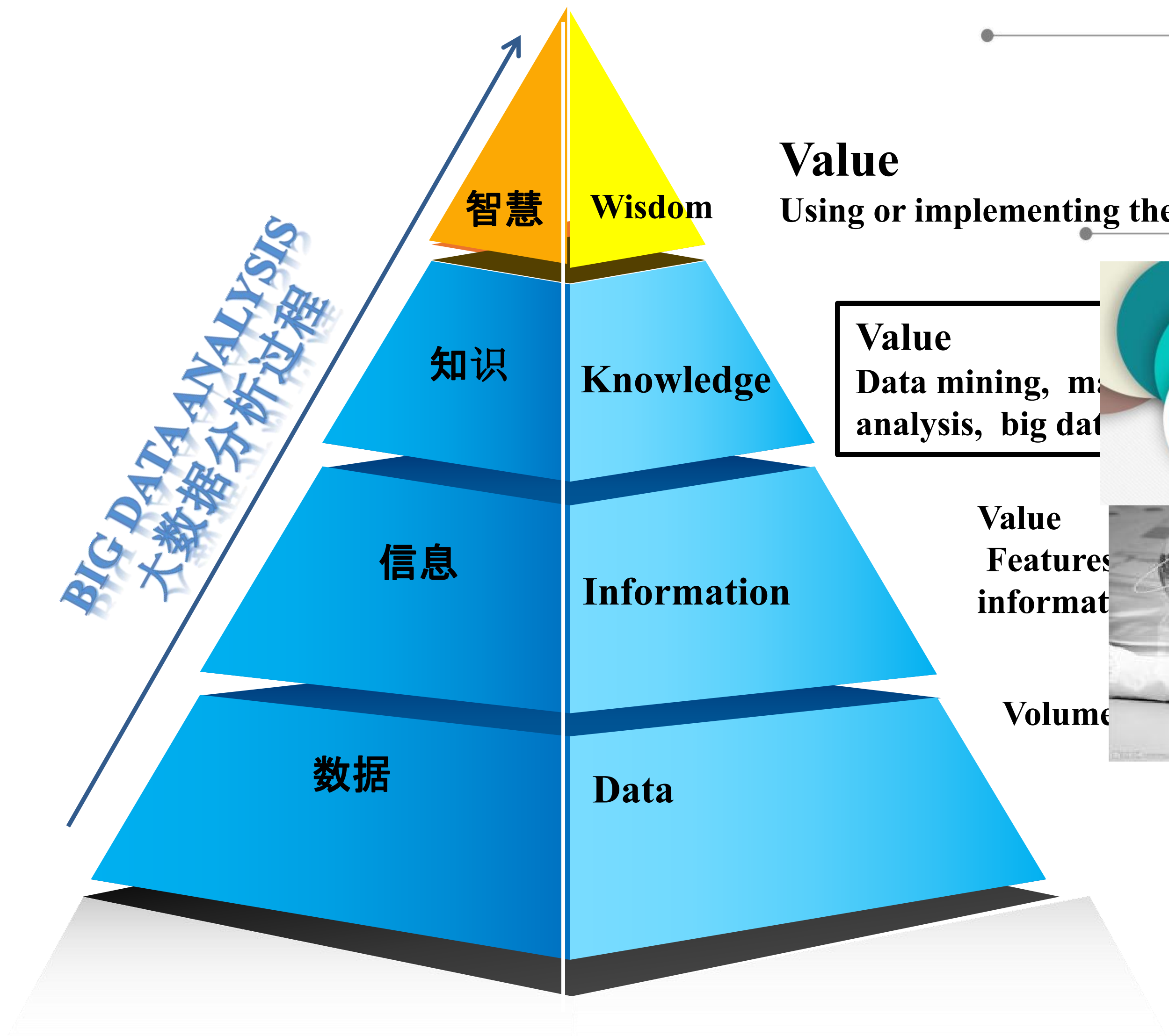
Value
Using or implementing the knowledge

Value
Data mining, machine learning, correlation analysis, big data analytics, …

Value
Features, models of presentation, information fusion & integration, …

Volume, Velocity, Variety, 。。。

Data-information-Knowledge-Wisdom



Value
Using or implementing the knowledge

Value
Data mining, ma
analysis, big dat

Value
Features
informat

Volume

Acknowledgement

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Prof. Hua Wang, Dr. Siuly Siuly, Dr. Jiangang Ma;

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\+

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