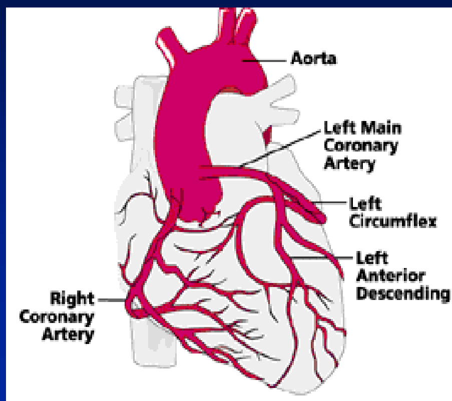
ECG SIGNAL RECOGNIZATION AND APPLICAITIONS

ECE, UA

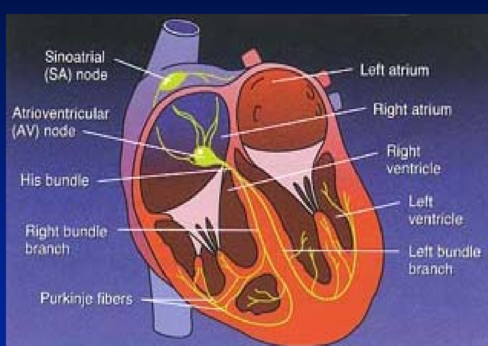
12 Lead ECG Interpretation

Anatomy Revisited



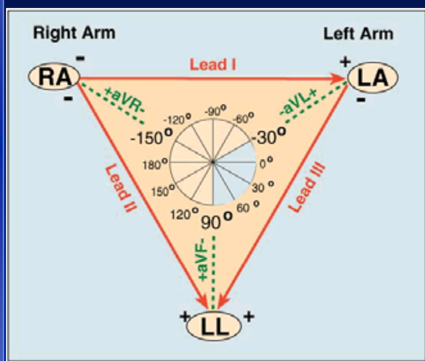
- RCA
  - right ventricle
  - inferior wall of LV
  - posterior wall of LV (75%)
  - SA Node (60%)
  - AV Node (>80%)
- LCA
  - septal wall of LV
  - anterior wall of LV
  - lateral wall of LV
  - posterior wall of LV (10%)

Anatomy Revisited



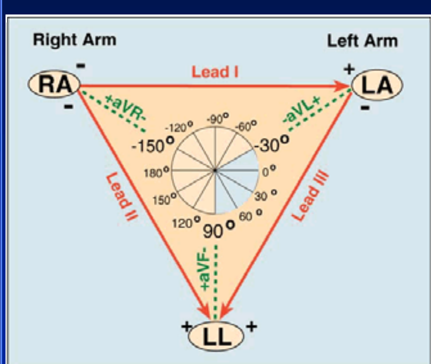
- SA node
- Intra-atrial pathways
- AV node
- Bundle of His
- Left and Right bundle branches
  - left anterior fascicle
  - left posterior fascicle
- Purkinje fibers

Bipolar Leads



- 1 positive and 1 negative electrode
  - RA always negative
  - LL always positive
- Traditional limb leads are examples of these
  - Lead I
  - Lead II
  - Lead III
- View from a vertical plane

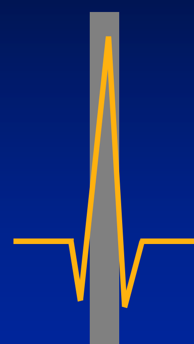
Unipolar Leads



- 1 positive electrode & 1 negative "reference point"
  - calculated by using summation of 2 negative leads
- Augmented Limb Leads
  - aVR, aVF, aVL
  - view from a vertical plane
- Precordial or Chest Leads
  - V1-V6
  - view from a horizontal plane

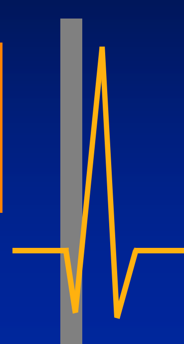
Waveform Components: R Wave

First positive deflection; R wave includes the downstroke returning to the baseline



Waveform Components: Q Wave

First negative deflection before R wave; Q wave includes the negative downstroke & return to baseline



Waveform Components: S Wave

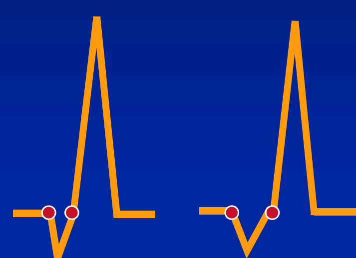
Negative deflection following the R wave; S wave includes departure from & return to baseline

Waveform Components: QRS

- Q waves
  - Can occur normally in several leads
    - Normal Q waves called physiologic
  - Physiologic Q waves
    - < .04 sec (40ms)
  - Pathologic Q
    - ≥.04 sec (40 ms)

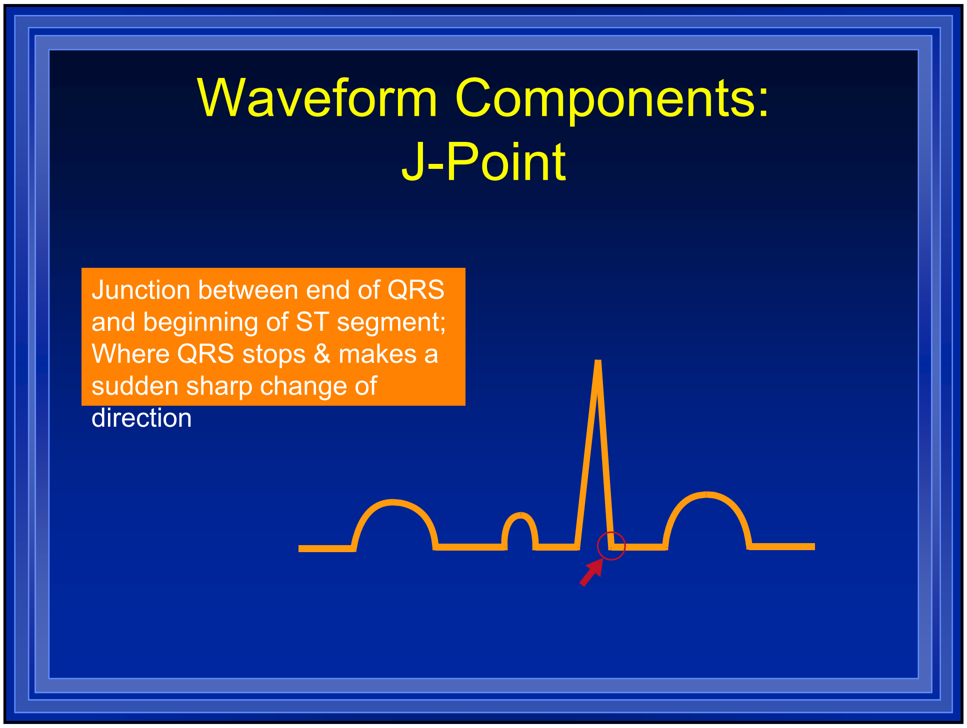
Waveform Components: QRS

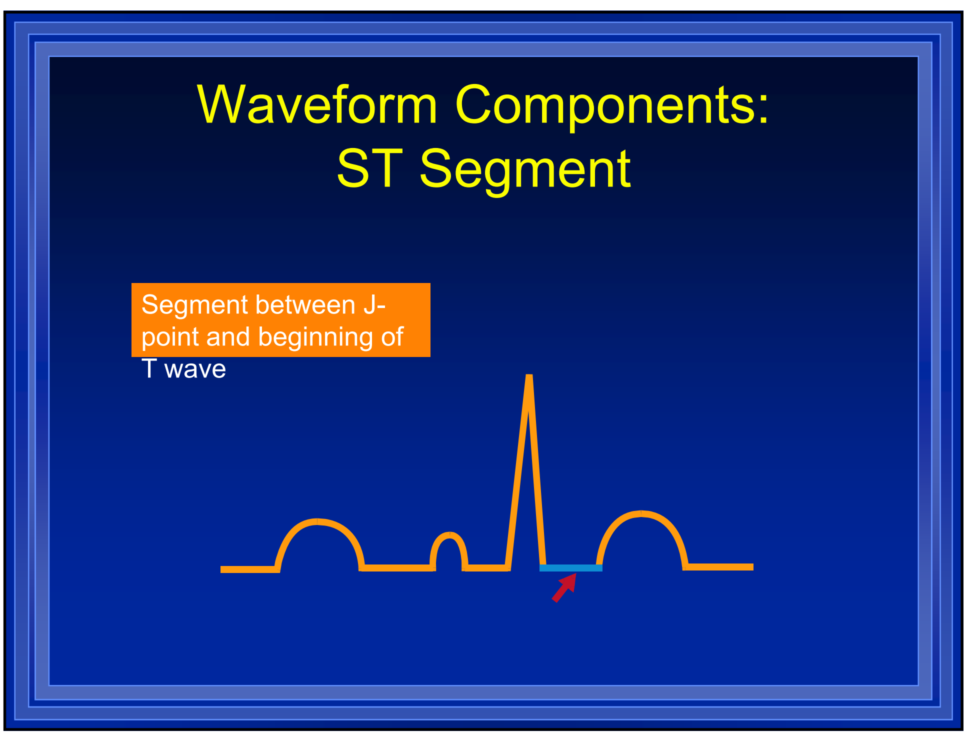
- Q wave
  - Measure width
  - Pathologic if greater than or equal to 0.04 seconds (1 small box)



Waveform Components: QS Complex

Entire complex is negatively deflected; No R wave present


Waveform Components:
J-Point
Junction between end of QRS and beginning of ST segment; Where QRS stops & makes a sudden sharp change of direction


Waveform Components:
ST Segment
Segment between J-point and beginning of T wave

Lead Groups

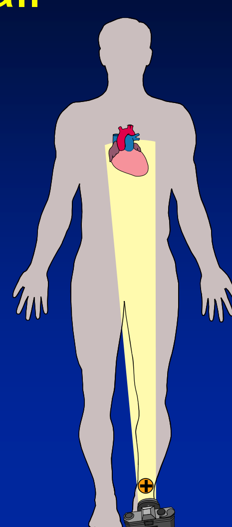
I	aVR	V1	V4
II	aVL	V2	V5
III	aVF	V3	V6

Limb Leads | **Chest Leads**

Inferior Wall

- II, III, aVF
  - View from Left Leg ⊕
  - inferior wall of left ventricle

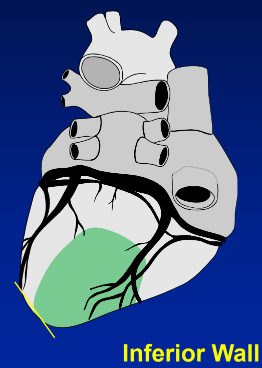
I	aVR	V1	V4
II	aVL	V2	V5
III	aVF	V3	V6



Inferior Wall

- Posterior View
  - portion resting on diaphragm
  - ST elevation ❑ suspect inferior injury

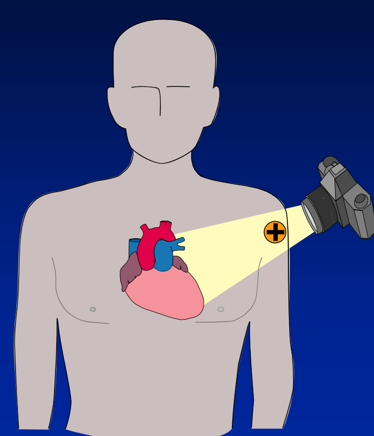
I	aVR	V1	V4
II	aVL	V2	V5
III	aVF	V3	V6



Lateral Wall

- I and aVL
  - View from Left Arm ⊕
  - lateral wall of left ventricle

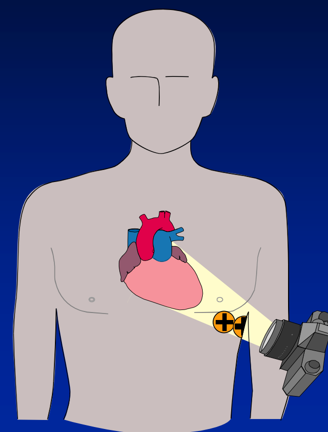
I	aVR	V1	V4
II	aVL	V2	V5
III	aVF	V3	V6



Lateral Wall

- V5 and V6
  - Left lateral chest
  - lateral wall of left ventricle

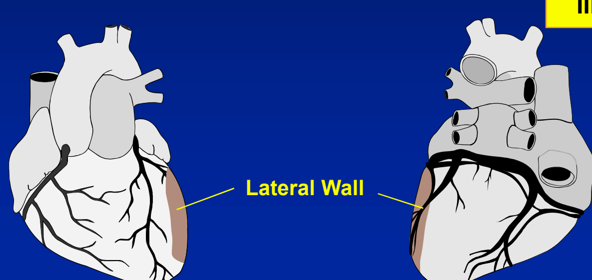
I	aVR	V1	V4
II	aVL	V2	V5
III	aVF	V3	V6



Lateral Wall

- I, aVL, V5, V6
  - ST elevation ❑ suspect lateral wall injury

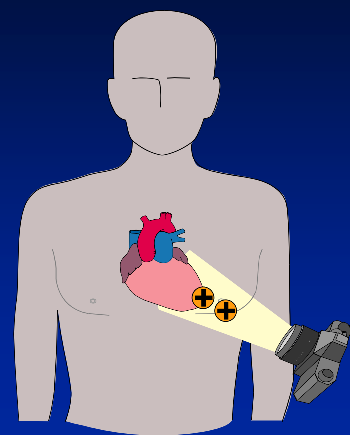
I	aVR	V1	V4
II	aVL	V2	V5
III	aVF	V3	V6



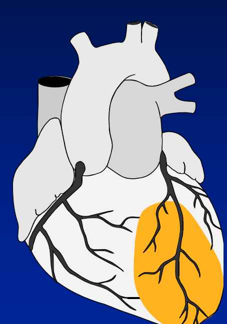
Anterior Wall

- V3, V4
  - Left anterior chest
  - ⊕ electrode on anterior chest

I	aVR	V1	V4
II	aVL	V2	V5
III	aVF	V3	V6



Anterior Wall

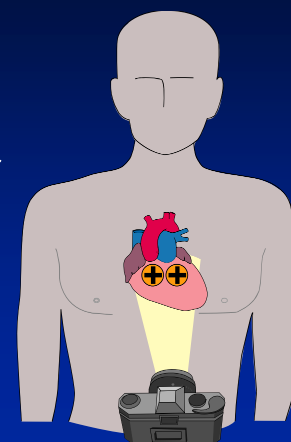


- V3, V4
  - ST segment elevation ❑ suspect anterior wall injury

I	aVR	V1	V4
II	aVL	V2	V5
III	aVF	V3	V6

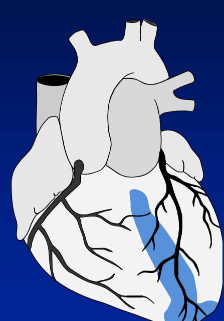
Septal Wall

- V1, V2
  - Along sternal borders
  - Look through right ventricle & see septal wall



I	aVR	V1	V4
II	aVL	V2	V5
III	aVF	V3	V6

Septal



- V1, V2
  - septum is left ventricular tissue

I	aVR	V1	V4
II	aVL	V2	V5
III	aVF	V3	V6

Axis Deviation&Bundle Branch Blocks

- Review of Leads
- EKG Leads
  - EKG machines record the electrical activity
    - Bipolar limb leads and augmented limb leads [I,II,III, aVR,aVL,aVF] comprise the FRONTAL PLANE LEADS
      - Records the electrical activity of the hearts frontal plane and are measured from the top of the heart to the bottom of the heart [right to left]

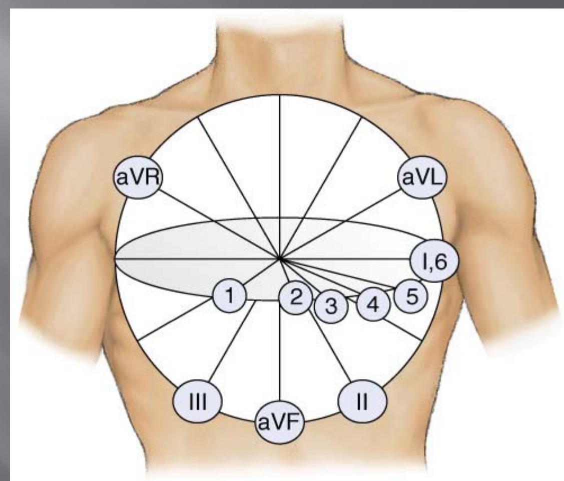
Review of Leads

- EKG Leads, continued
  - EKG machines record the electrical activity.
    - Precordial leads or chest leads [V1, V2, V3, V4, V5, V6] view the hearts horizontal plane
    - The heart acts as a central point of the cross section and the electrical current flows from the central point out to each of the V leads

12-Lead View in perspectives

Axis Deviation

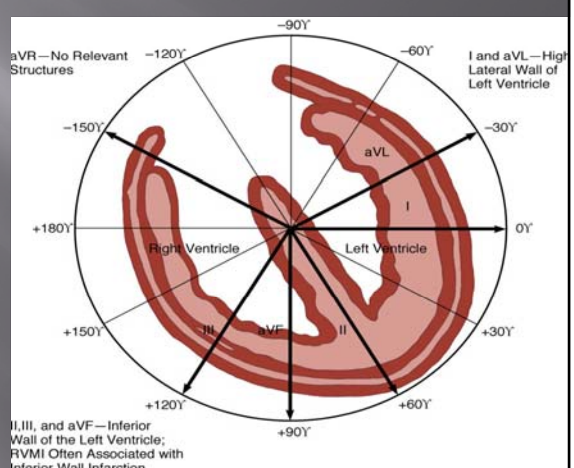
Bundle Branch Blocks



Understanding 12 Lead EKGS 27

The Hexaxial Reference System

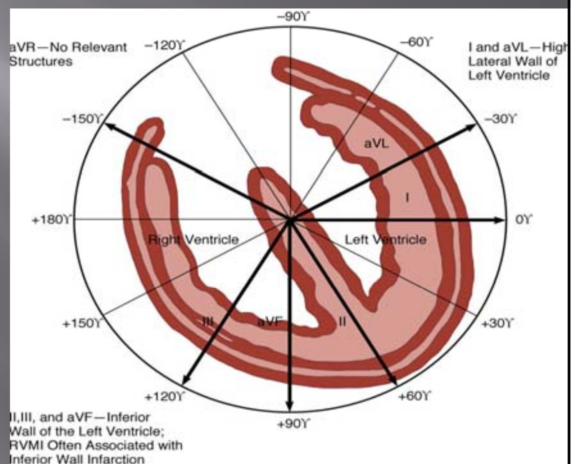
- It is divided into positive and negative sections
- The direction of the left arm starts at 0 degrees and continues clockwise in 30 degree increments until it reaches 180 degrees
- It then begins to measure in the negative range until it returns to 0



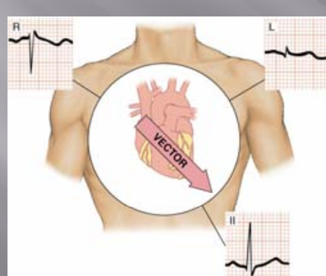
BRADY: Understanding 12 Lead EKGS
Ch. 14 28

The Hexaxial Reference System

- It is utilized to calculate the exact axis of the heart
- In the emergent situation, the exact degree of axis is less important then determining the presence of any deviation in the axis



Axis Deviation



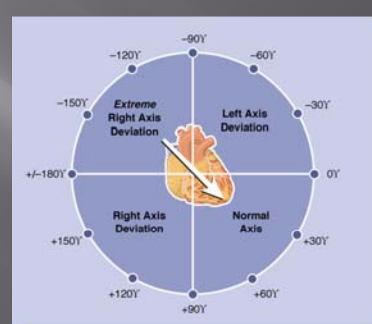
- Terms:
  - Vector : a mark or symbol used to describe any force having both magnitude and direction; the direction of electrical currents in cardiac cells that are generated by depolarization and repolarization
  - The currents spread from the endocardium outward to the epicardium

Axis Deviation

- Lead axis : the axis of a given lead
- Mean QRS axis : the mean [average] of all ventricular vectors is a single large vector with a mean QRS axis, usually pointing to the left and downward

Axis Deviation

- Axis deviation – alteration in normal flow of current that represents an abnormal ventricular depolarization pathway and may signify death or disease of the myocardium

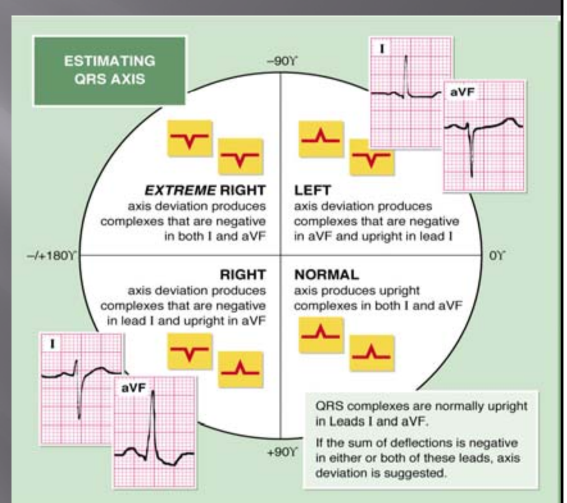


Axis Deviation

- Axis deviation – Mean axis most commonly flows from top to bottom or right to left
- Mean axis commonly flows to a point of +30 degrees
- When heart is enlarged, or due to disease or death of muscle, conduction pattern is altered or deviated = axis deviation

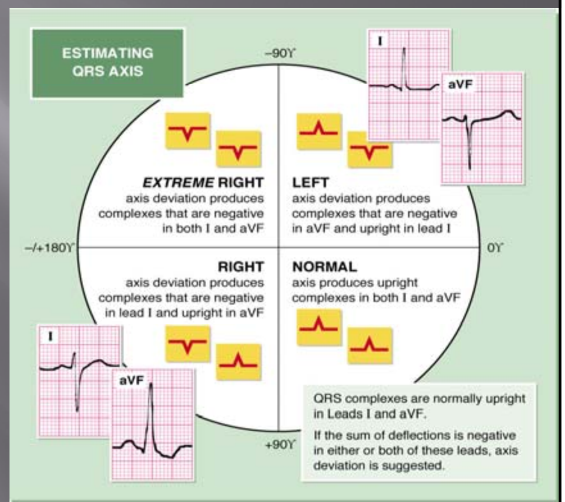
Axis Deviation

- Right Axis deviation- Deviation is between +90 degrees and + or – 180 degrees
- Lead 1 = **- QRS** deflection
- Lead aVF = **+ QRS** deflection



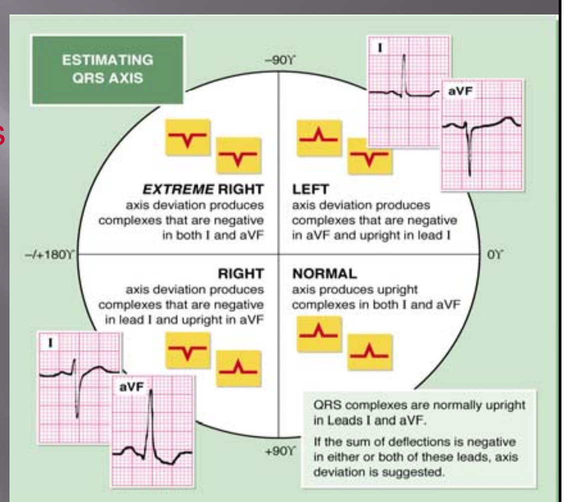
Axis Deviation

- Left Axis deviation– Deviation is between 0 and – 90 degrees
- Lead 1 = **+ QRS** deflection
- Lead aVF = **- QRS** deflection



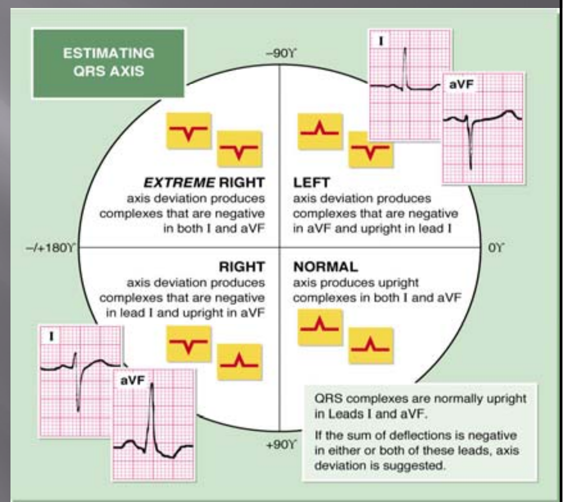
Axis Deviation

- Extreme right or indeterminate Axis deviation – Deviation is between - 90 and + or – 180 degrees
- Lead 1 = **- QRS** deflection
- Lead aVF = **- QRS** deflection



Axis Deviation

- Normal Axis
- Lead 1 = + **QRS** deflection
- Lead aVF = + **QRS** deflection



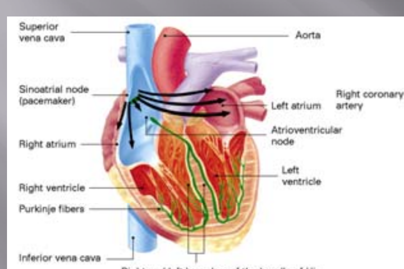
Axis deviation may be caused by:

- Right Axis Deviation
  - COPD
  - Pulmonary embolism
  - Congenital heart disease
  - Pulmonary hypertension
  - Cor pulmonale
- Left Axis Deviation
  - Ischemic heart disease
  - Systemic hypertension
  - Aortic stenosis
  - Disorders of left ventricle
  - Aortic valvular disease
  - Wolff-Parkinson-White syndrome

Bundle Branch Blocks

- Right Bundle Branches
  - Runs down right side of interventricular septum and terminates at papillary muscles
  - Functions to carry electrical impulses to the right ventricle
- Left Bundle Branches
  - Shorter then the right bundle branch
  - Divides into pathways that spread throughout the left side of the interventricular septum and throughout the left ventricle
  - Two main divisions are called fascicles

Bundle Branch Blocks



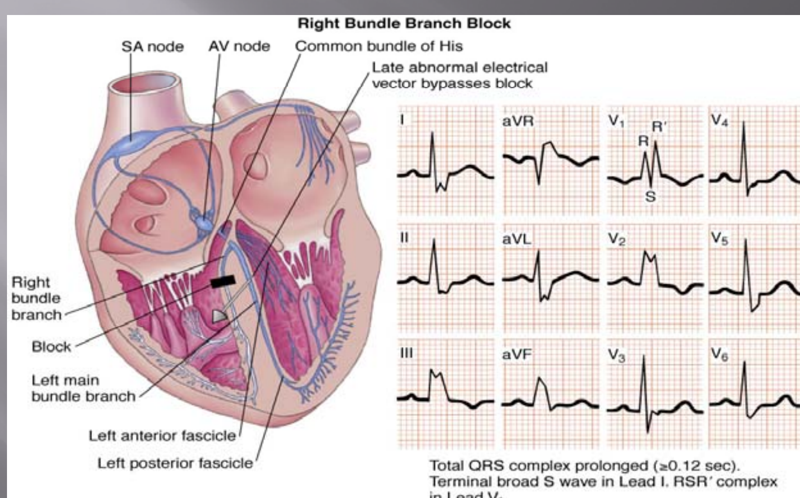
- Normal Conduction
  - Impulse travels simultaneously through the right bundle branch and left bundle branch
  - Causing depolarization of interventricular septum and left and right ventricles

Bundle Branch Blocks

- When one bundle branch is blocked:
  - Electrical impulse will travel through intact branch and stimulate ventricle supplied by that branch
  - Ventricle effected by blocked or defective bundle branch is activated indirectly
  - There is a delay caused by this alternate route
  - QRS complex will represent widening beyond usual time interval of 0.12 sec
  - Classified as either complete [**QRS measures 0.12 sec or greater**] or incomplete blocks [**QRS measures between 0.10 and 0.11 second**]

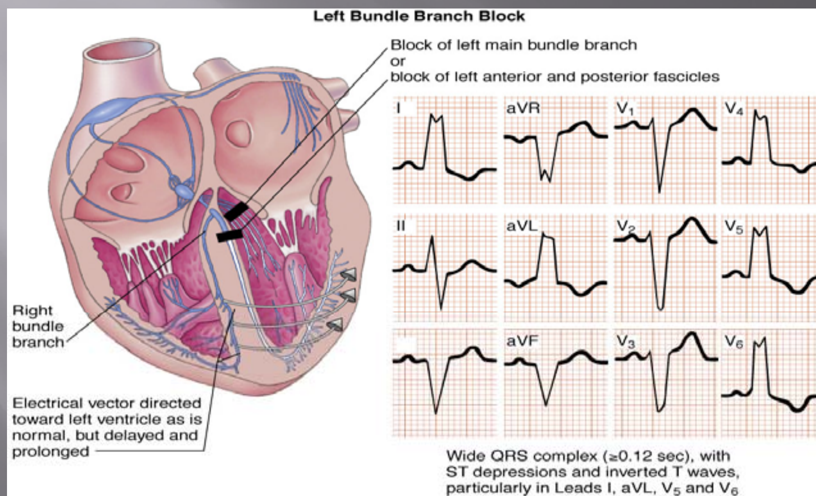
Understanding 12 Lead 41

Right Bundle Branch Block



Understanding 12 Lead EKGS 42

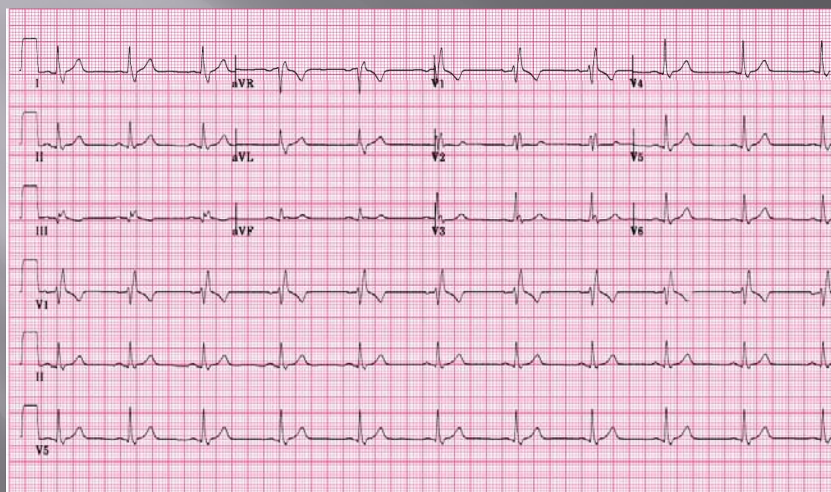
Left Bundle Branch Block



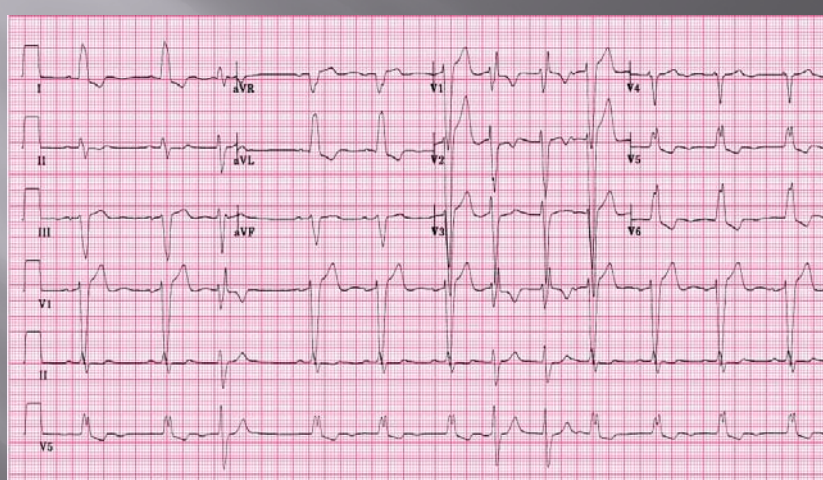
Clinical Significance of Bundle Branch Blocks

- 15% to 30% of patients experiencing MI in conjunction with new-onset bundle branch blocks may develop complete block and estimated 30% to 70% may develop cardiogenic shock
- Cardiogenic shock carries an 85% mortality rate
- To determine presence of new-onset block, must have access to past 12-lead EKGs

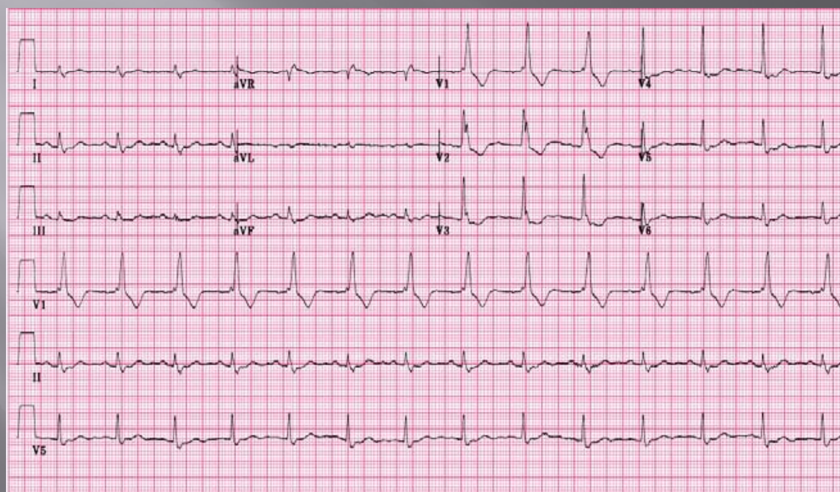
Right Bundle Branch Block with normal axis



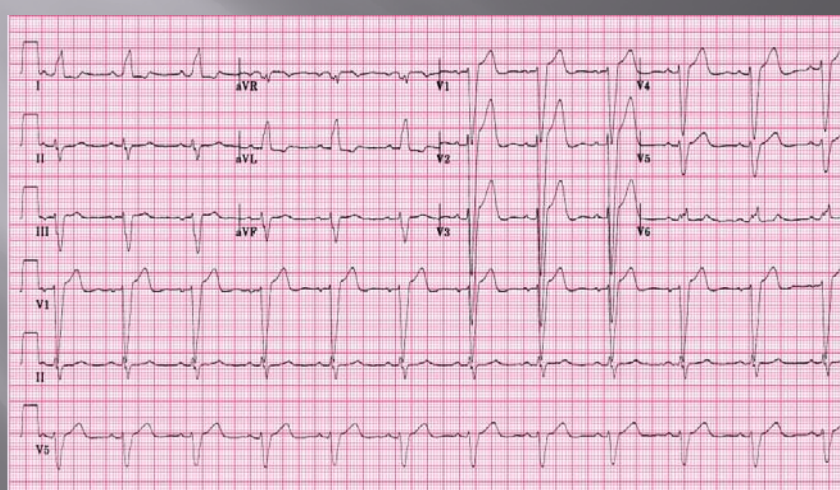
Left Bundle Branch Block with left axis deviation



Right Bundle Branch Block with normal axis deviation



Left Bundle Branch Block with left axis deviation



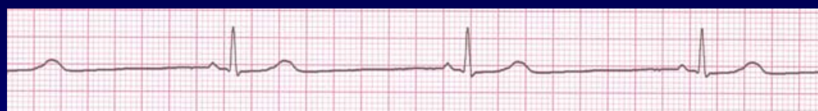
ECG Rhythm Interpretation

Sinus Rhythms and
Premature Beats

Arrhythmias

- Sinus Rhythms
- Premature Beats
- Supraventricular Arrhythmias
- Ventricular Arrhythmias
- AV Junctional Blocks

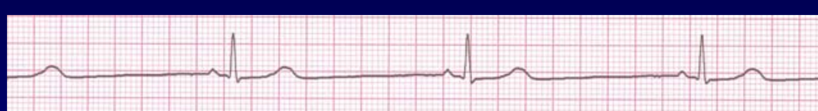
Rhythm #1



- Rate? 30 bpm
- Regularity? regular
- P waves? normal
- PR interval? 0.12 s
- QRS duration? 0.10 s

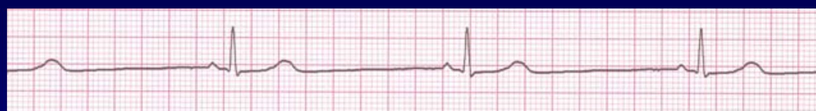
Interpretation? *Sinus Bradycardia*

Sinus Bradycardia



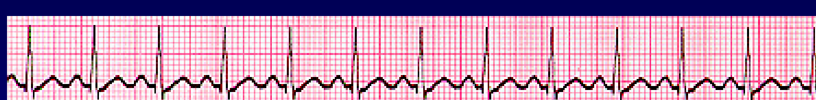
- Deviation from NSR
  - Rate < 60 bpm

Sinus Bradycardia



- Etiology: SA node is depolarizing slower than normal, impulse is conducted normally (i.e. normal PR and QRS interval).

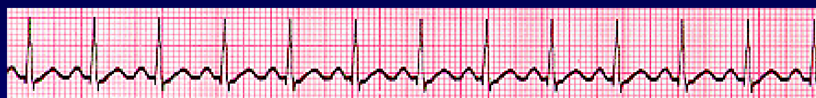
Rhythm #2



• Rate?	130 bpm
• Regularity?	regular
• P waves?	normal
• PR interval?	0.16 s
• QRS duration?	0.08 s

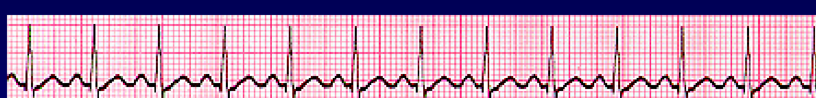
Interpretation? *Sinus Tachycardia*

Sinus Tachycardia



- Deviation from NSR
  - Rate > 100 bpm

Sinus Tachycardia

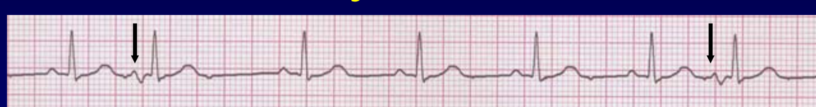


- Etiology: SA node is depolarizing faster than normal, impulse is conducted normally.
- Remember: sinus tachycardia is a response to physical or psychological stress, not a primary arrhythmia.

Premature Beats

- *Premature Atrial Contractions (PACs)*
- *Premature Ventricular Contractions (PVCs)*

Rhythm #3



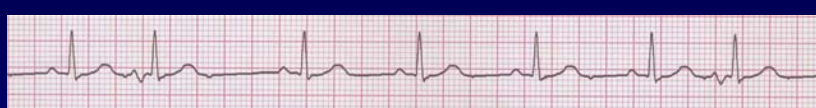
• Rate?	70 bpm
• Regularity?	occasionally irreg.
• P waves?	2/7 different contour
• PR interval?	0.14 s (except 2/7)
• QRS duration?	0.08 s

Interpretation? *NSR with Premature Atrial Contractions*

Premature Atrial Contractions

- Deviation from NSR
  - These ectopic beats originate in the atria (but not in the SA node), therefore the contour of the P wave, the PR interval, and the timing are different than a normally generated pulse from the SA node.

Premature Atrial Contractions



- Etiology: Excitation of an atrial cell forms an impulse that is then conducted normally through the AV node and ventricles.

Teaching Moment

- When an impulse originates anywhere in the atria (SA node, atrial cells, AV node, Bundle of His) and then is conducted normally through the ventricles, the QRS will be narrow (0.04 - 0.12 s).

Rhythm #4

- Rate? 60 bpm
- Regularity? occasionally irreg.
- P waves? none for 7th QRS
- PR interval? 0.14 s
- QRS duration? 0.08 s (7th wide)

Interpretation? *Sinus Rhythm with 1 PVC*

PVCs

- Deviation from NSR
  - Ectopic beats originate in the ventricles resulting in wide and bizarre QRS complexes.
  - When there are more than 1 premature beats and look alike, they are called “uniform”. When they look different, they are called “multiform”.

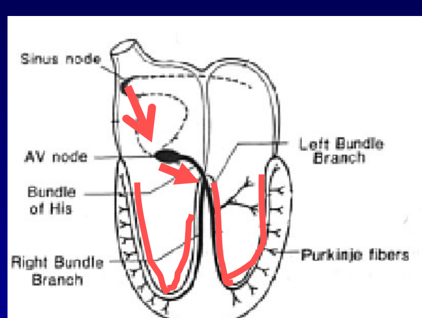
PVCs

- Etiology: One or more ventricular cells are depolarizing and the impulses are abnormally conducting through the ventricles.

Teaching Moment

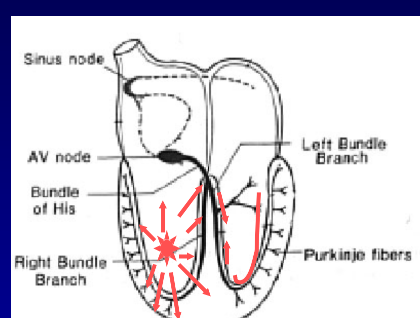
- When an impulse originates in a ventricle, conduction through the ventricles will be inefficient and the QRS will be wide and bizarre.

Ventricular Conduction



Normal

Signal moves rapidly through the ventricles

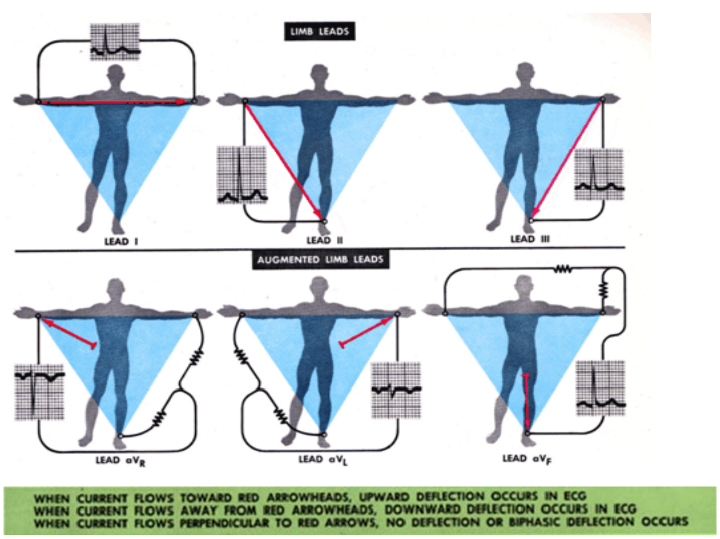


Abnormal

Signal moves slowly through the ventricles

ECG Clues to Identify the Site of Occlusion in Acute Myocardial Ischemia/Infarction

Limb Leads and Augmented Limb Leads



Direction of ST Vector and ECG Changes in Proximal LAD Occlusion

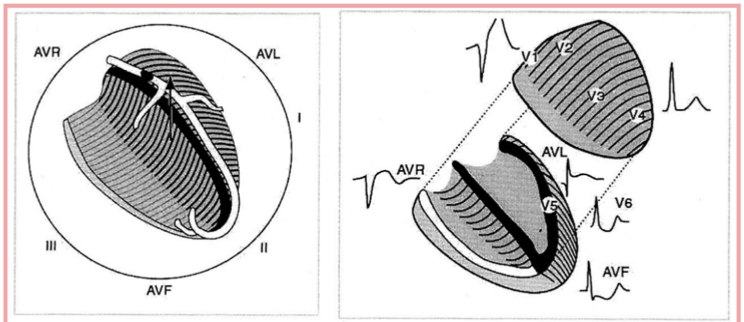
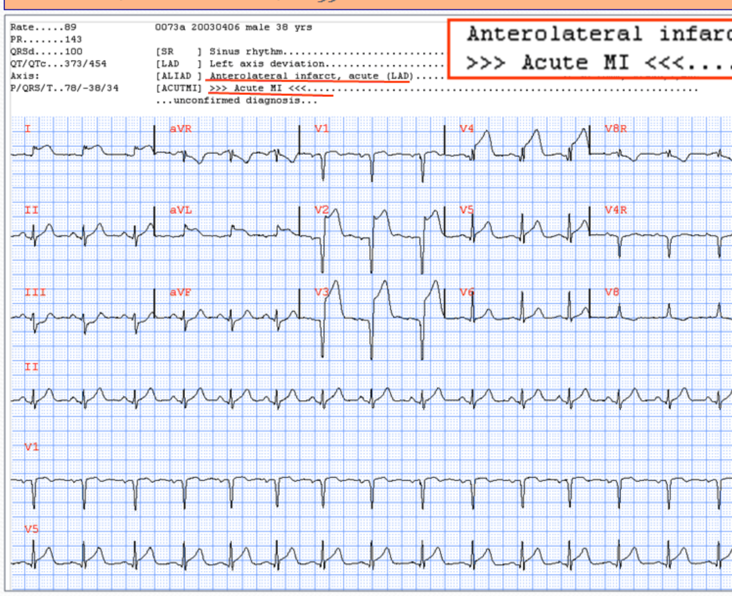
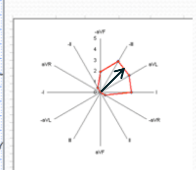


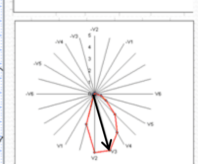
Figure 2.16
Left panel: Proximal LAD occlusion.
Global ischemia of the whole anterior and septal aspect of the left ventricle. The ST segment vector points in a superior direction, because the anterobasal segment is the dominant ischemic area.
Right panel: Related ECG changes.
The superiorly oriented ST vector leads to ST changes, such as ST elevation in lead AVR and V_1 with reciprocal ST depression in the inferior leads and in leads V_5 and V_6.

Example 1: (#0073) 38 years old male, Asian, chest pain 9 h, TnI 3.4 at admission, LAD occlusion, EF 35%



ST-MAP

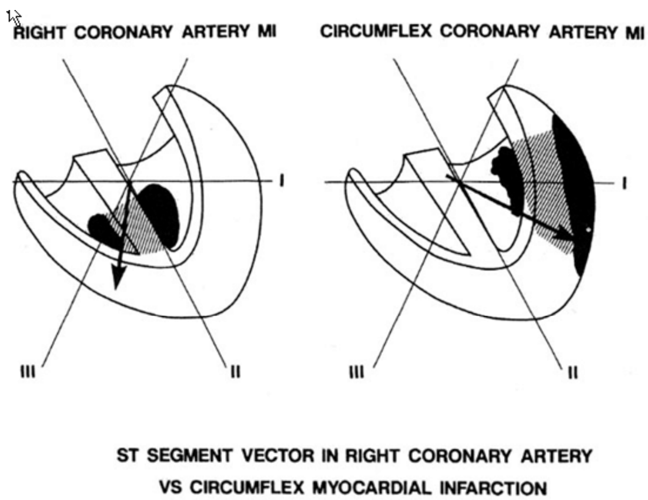




3

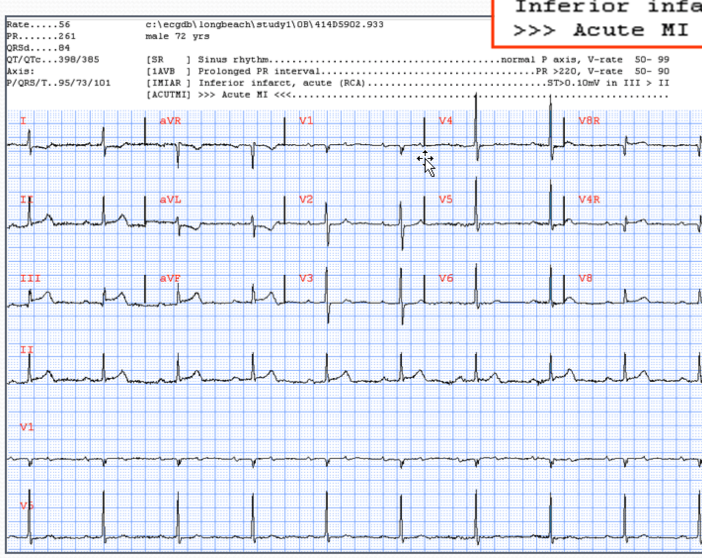
Direction of ST Vector in RCA and LCX Occlusion

Figure 2.4
Schematic presentation of the ST-segment vector in inferior wall infarction. In RCA-occlusion an inferior and rightward orientation towards lead III and in CX occlusion an inferior and leftward orientation towards lead II is present.

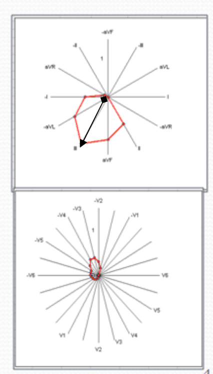


Example 8: (#103) 72 years old male, Asian, Chest pain 5 hours, TnL < 0.1 at admission, proximal RCA occlusion

Inferior infarct, acute (RCA)
>>> Acute MI <<<.............



ST-MAP



ECG Criteria for Identifying Culprit Lesion

Left main: ST depression in seven or more leads with ST elevation, aVR and V1 at rates less than 100bpm and no LVH

Proximal LAD: ST elevation in lead 1, aVL, V1-3, 4. ST depression in lead 3 and sometimes lead 2

Non-proximal LAD: ST elevation V3-6 but not aVL and no ST depression in leads 2 or 3

Proximal RCA: ST elevation 2, 3, aVF, greater in 3 than in 2 with ST elevation in V4 R and V3R and ST depression in 1, aVL. ST changes in leads V1 and V2 depend on right ventricular and posterior wall involvement.

Non-proximal RCA: ST elevation 2, 3, aVF greater in 2 than in 3 but without ST elevation in V4R, V3R

LCX: ST elevation in leads 2, 3 aVF. ST depression in leads V1 and V2

Test of Criteria for Identifying Culprit Lesion

	n	Specificity	Sensitivity	PPV	NPV
LM	11	100%	64%	100%	97%
LADP	19	95%	63%	67%	94%
LADN	26	92%	65%	68%	91%
LCX	13	94%	46%	46%	94%
RCAP	28	86%	89%	64%	97%
RCAN	26	97%	46%	80%	88%
LM/LADP	30	95%	67%	80%	90%
LM/LADP/RCAP	58	74%	79%	72%	81%

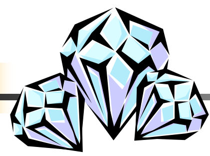
Conclusions

- ST segment depression is always the reciprocal of ST elevation and, conversely, ST elevation will always be accompanied by ST depression somewhere.
- By recognizing leads with ST depression as well as elevation, the location of a culprit lesion can be predicted with considerable accuracy.

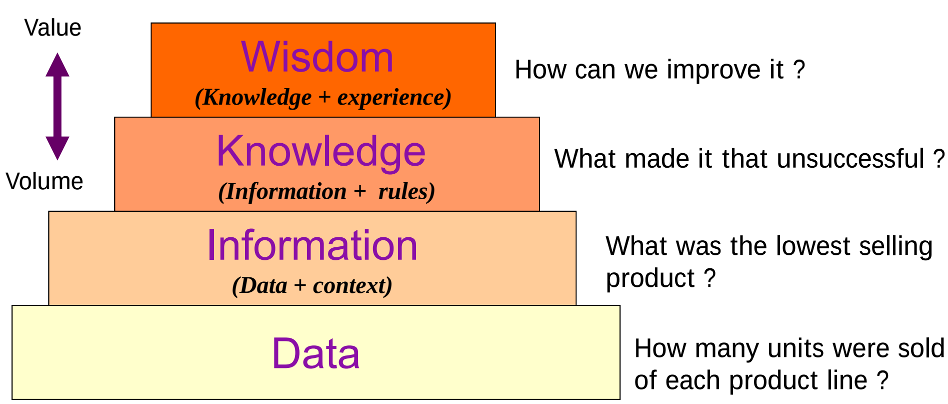
Conclusions (Continued)

- Recording of Leads V3R, V4R and V8 (and/or V9) are very helpful and should be done in all patients with inferior infarctions.
- Visualization of the spatial orientation of the ST segment vector enhances your ability to localize the site of occlusion.

Data Mining and Medical Informatics



The Data Pyramid



Data Mining Functions

Clustering into 'natural' groups (unsupervised)
Classification into known classes; e.g. diagnosis (supervised)
Detection of associations; e.g. in basket analysis: "70% of customers buying bread also buy milk"
Detection of sequential temporal patterns; e.g. disease development
Prediction or estimation of an outcome
Time series forecasting

Data Mining Techniques (box of tricks)

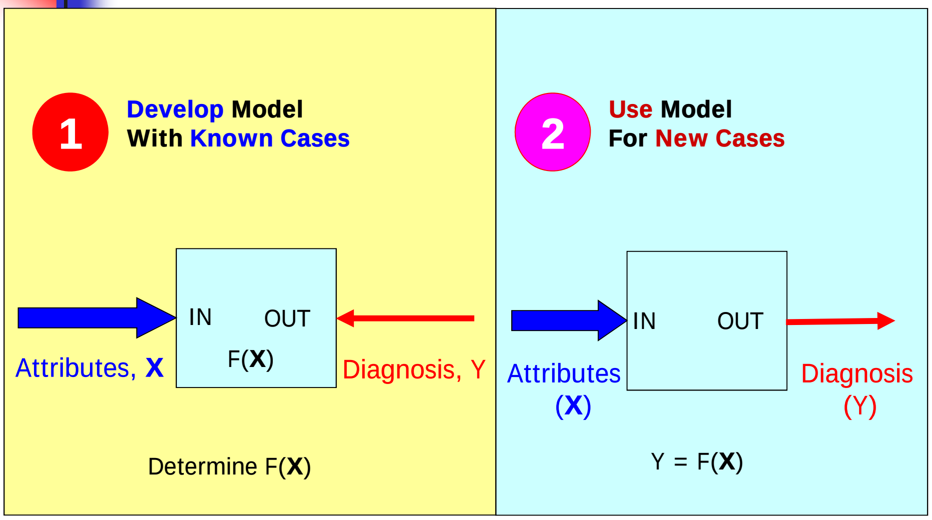
Statistics
Linear Regression
Visualization
Cluster analysis

Older,
Data preparation,
Exploratory

Decision trees
Rule induction
Neural networks
Abductive networks

Newer, Modeling,
Knowledge Representation

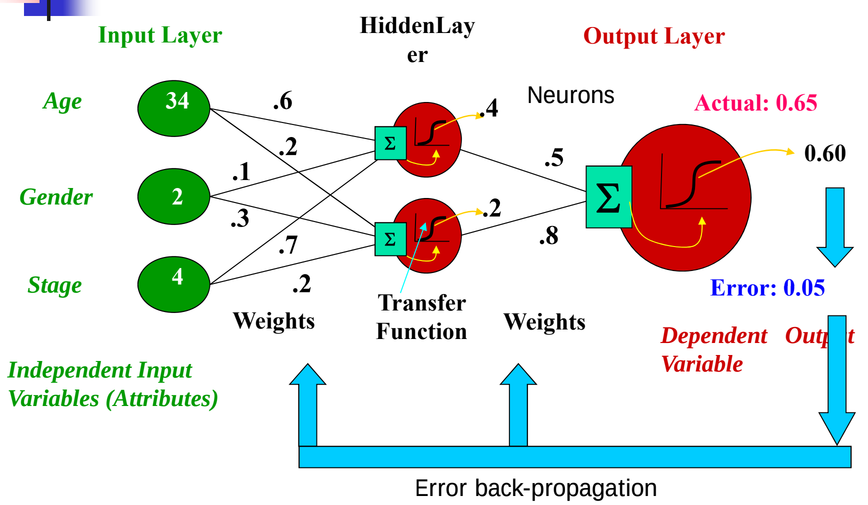
Data-based Predictive Modeling



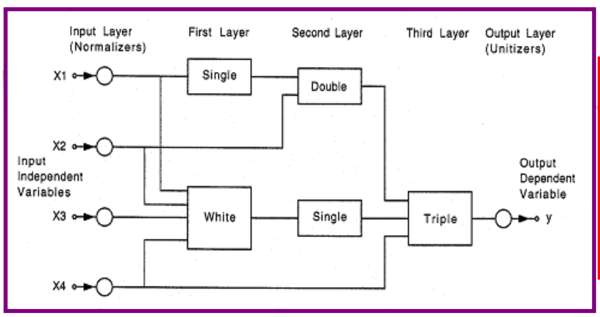
Data-based Predictive Modeling by supervised Machine learning

- Database of solved examples (input-output)
- Preparation: cleanup, transform, add new attributes...
- Split data into a training and a test set
- Training:
  Develop model on the training set
- Evaluation:
  See how the model fares on the test set
- Actual use:
  Use successful model on new input data to estimate unknown output

The Neural Network (NN) Approach



Self-Organizing Abductive (Polynomial) Networks



"Double" Element:

$$y = w0 + w1\ x1 + w2\ x2 + w3\ x1^2 + w4\ x2^2 + w5\ x1\ x2 + w6\ x1^3 + w7\ x2^3$$

- Network of polynomial functional elements- not simple neurons
- No fixed *a priori* model structure. Model evolves with training
- Automatic selection of: Significant inputs, Network size, Element types, Connectivity, and Coefficients
- Automatic stopping criteria, with simple control on complexity
- Analytical input-output relationships

Medicine revolves on Pattern Recognition, Classification, and Prediction

Diagnosis:
Recognize and classify patterns in multivariate patient attributes

Therapy:
Select from available treatment methods; based on effectiveness, suitability to patient, etc.

Prognosis:
Predict future outcomes based on previous experience and present conditions

Need for Data Mining in Medicine

Nature of medical data: noisy, incomplete, uncertain, nonlinearities, fuzziness $\Rightarrow$ Soft computing

Too much data now collected due to computerization (text, graphs, images,...)

Too many disease markers (attributes) now available for decision making

Increased demand for health services: (Greater awareness, increased life expectancy, ...)

- Overworked physicians and facilities

Stressful work conditions in ICUs, etc.

Medical Applications

- Screening
- Diagnosis
- Therapy
- Prognosis
- Monitoring
- Biomedical/Biological Analysis
- Epidemiological Studies
- Hospital Management
- Medical Instruction and Training

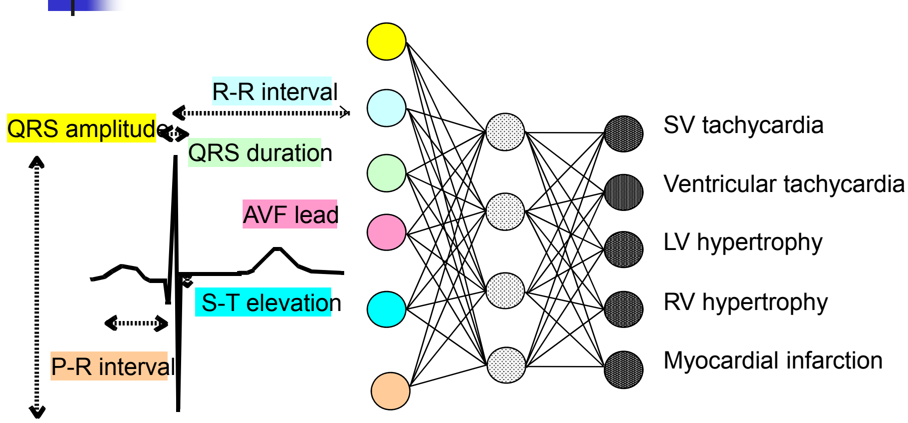
Medical Screening

- Effective low-cost screening using disease models that require easily-obtained attributes:
  (historical, questionnaires, simple measurements)
- Reduces demand for costly specialized tests
  (Good for patients, medical staff, facilities, …)
- Examples:
  - Prostate cancer using blood tests
  - Hepatitis, Diabetes, Sleep apnea, etc.

Diagnosis and Classification

- Assist in decision making with a large number of inputs and in stressful situations
- Can perform automated analysis of:
  - Pathological signals (ECG, EEG, EMG)
  - Medical images (mammograms, ultrasound, X-ray, CT, and MRI)
- Examples:
  - Heart attacks, Chest pains, Rheumatic disorders
  - Myocardial ischemia using the ST-T ECG complex
  - Coronary artery disease using SPECT images

Diagnosis and Classification
ECG Interpretation



Therapy

- Based on modeled historical performance, select best intervention course:
  e.g. best treatment plans in radiotherapy
- Using patient model, predict optimum medication dosage: e.g. for diabetics
- Data fusion from various sensing modalities in ICUs to assist overburdened medical staff

Prognosis

- Accurate prognosis and risk assessment are essential for improved disease management and outcome

  Examples:
  - Survival analysis for AIDS patients
  - Predict pre-term birth risk
  - Determine cardiac surgical risk
  - Predict ambulation following spinal cord injury
  - Breast cancer prognosis

Biochemical/Biological Analysis

- Automate analytical tasks for:
  - Analyzing blood and urine
  - Tracking glucose levels
  - Determining ion levels in body fluids
  - Detecting pathological conditions

Epidemiological Studies

Study of health, disease, morbidity, injuries and mortality in human communities

- Discover patterns relating outcomes to exposures
- Study independence or correlation between diseases
- Analyze public health survey data
- Example Applications:
  - Assess asthma strategies in inner-city children
  - Predict outbreaks in simulated populations

Hospital Management

- Optimize allocation of resources and assist in future planning for improved services

Examples:

- Forecasting patient volume, ambulance run volume, etc.
- Predicting length-of-stay for incoming patients

Medical Instruction and Training

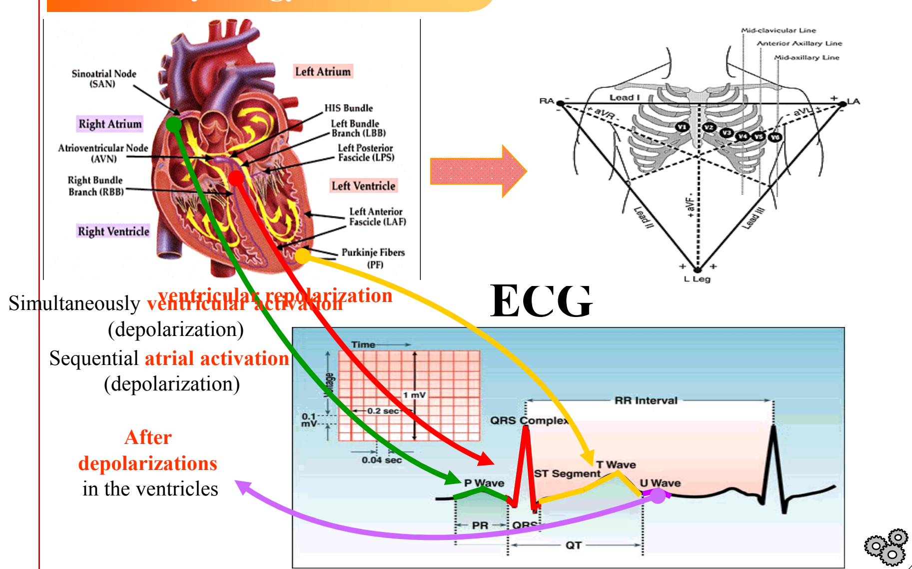
- Disease models for the instruction and assessment of undergraduate medical and nursing students
- Intelligent tutoring systems for assisting in teaching the decision making process

Benefits:

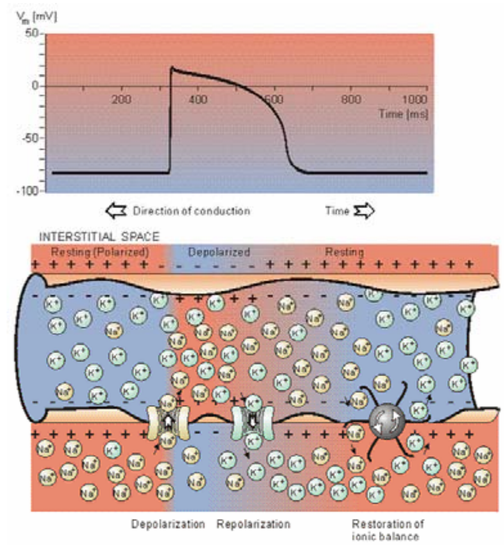
- Efficient screening tools reduce demand on costly health care resources
- Data fusion from multiple sensors
- Help physicians cope with the information overload
- Optimize allocation of hospital resources
- Better insight into medical survey data
- Computer-based training and evaluation

Biological Problem

Heart Physiology

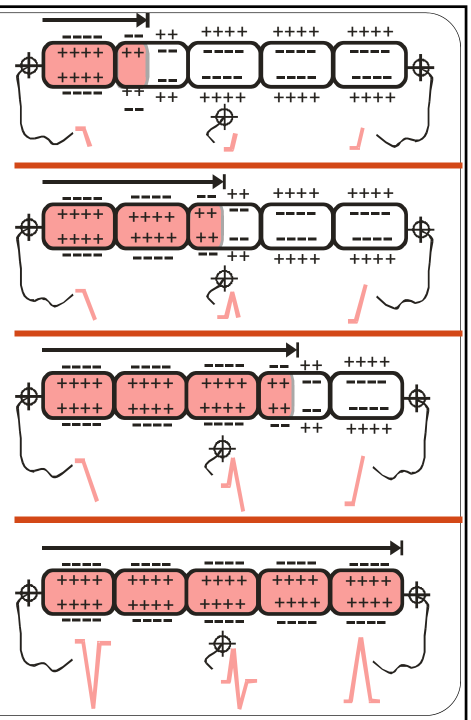


Electrophysiology of the cardiac muscle cell



Generation of the ECG complexes

A wave of depolarization moving toward an electrode will cause an upward deflection on the ECG needle.



Biological Problem

ECG wave shape characterization

Difference In Wave Shape And Frequency :

Normal

REGULAR RHYTHM

Arrhythmia

IRREGULAR RHYTHM

Ventricular Arrhythmia

P ,T AND U WAVE INDISTINCT. IRREGULAR RHYTHM

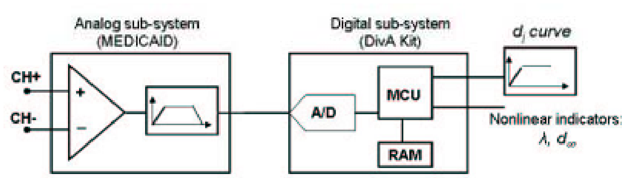
Bradycardia

REGULAR RHYTHM

The Algorithm

$$d_j = \frac{1}{N}\sum_{i=1}^{N} |x_j^{(i)} - x_j^{\prime(i)}|$$

$$d_\infty = \lim_{x\to\infty}\frac{1}{n}\sum_{j=1}^{n} d_j$$



The Algorithm

Input Parameters

Three Initial Conditions

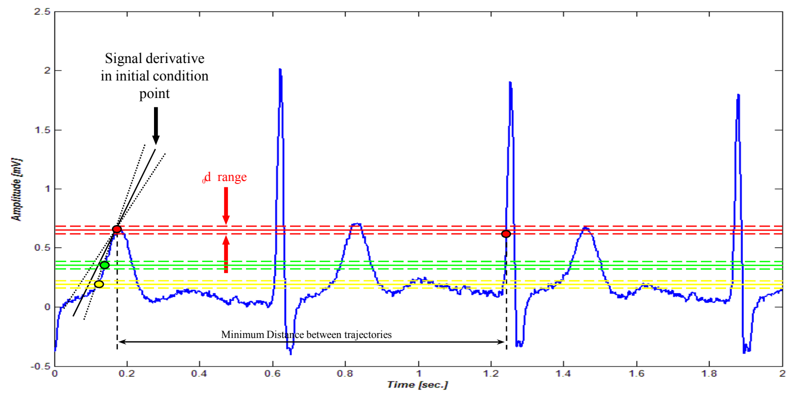
d_0 range

Signal derivative at the starting point

Number of Samples for Trajectors

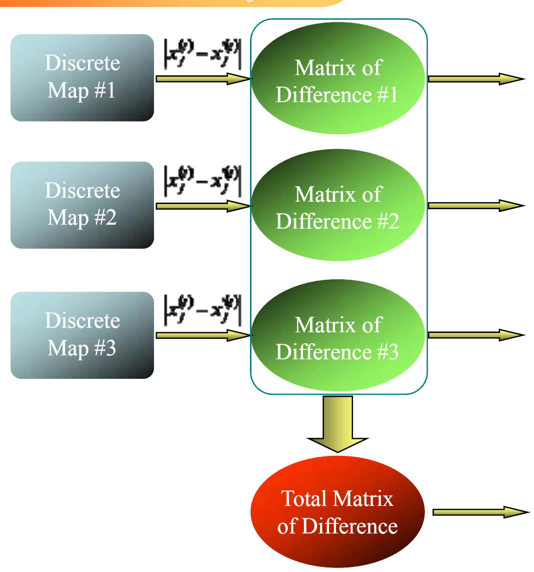
Minimum Distance between Trajectories

Number of couples of trajectories



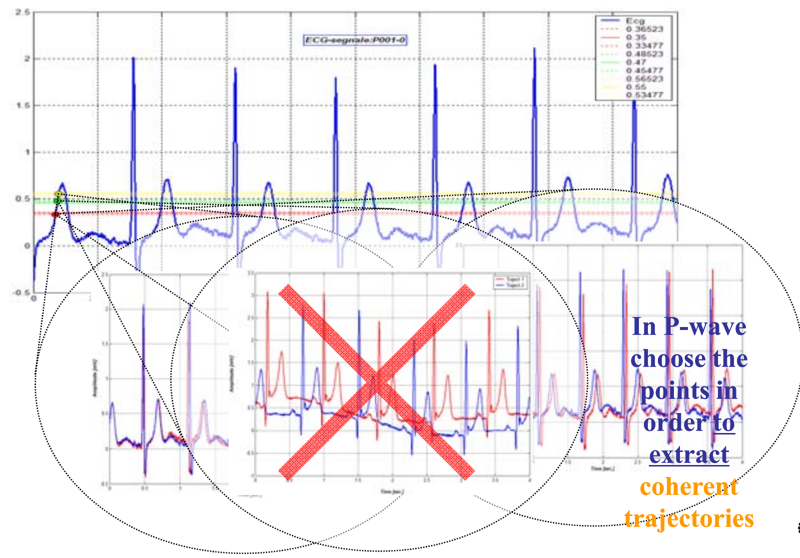
The Algorithm

From Discrete Map to d_j



Parametric Study

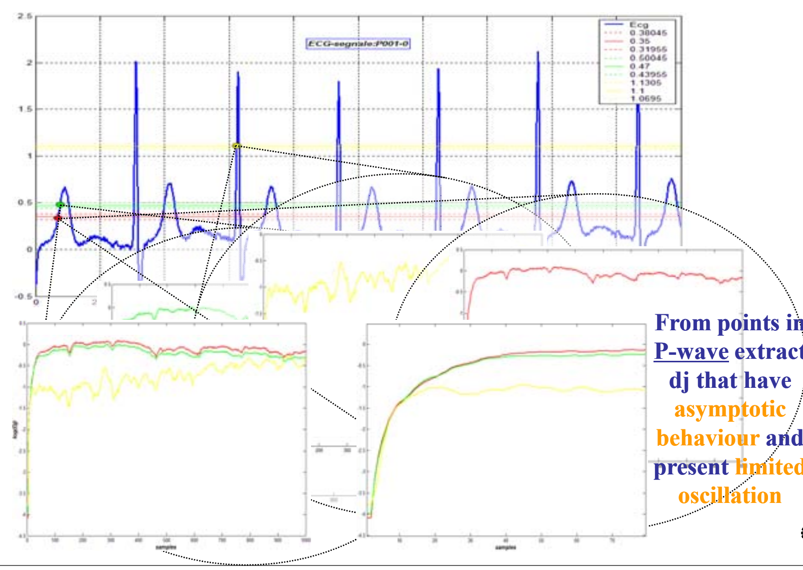
Initial Condition



In P-wave choose the points in order to extract coherent trajectories

Parametric Study

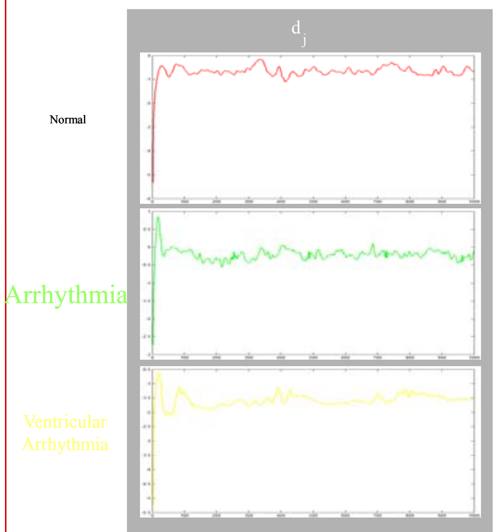
Extraction of dj parameters



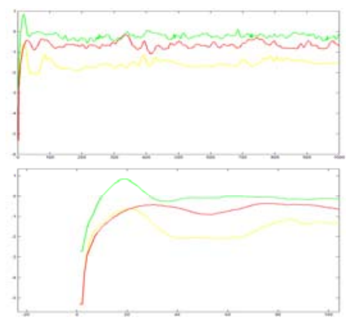
From points in P-wave extract dj that have asymptotic behaviour and present limited oscillation

Results

Trend of d_j

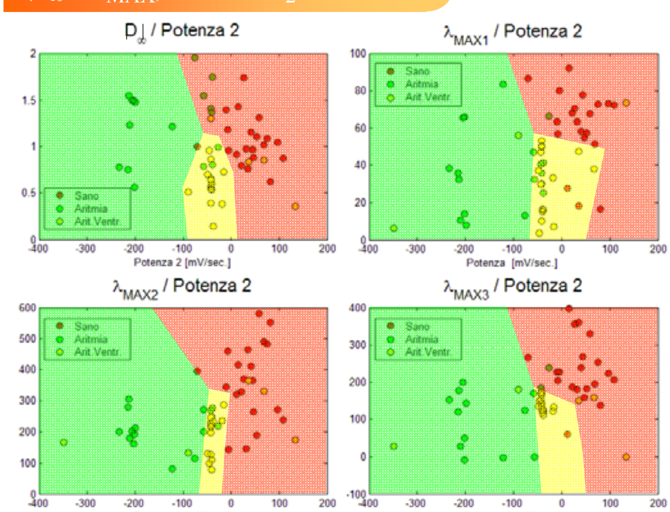


d_j have a **similar trend** for the three cases but with **different value.**



Results

$(d_\infty - \lambda_{MAX})$ vs $Power_2$



Normal

Arrhythmia

Ventricular Arrhythmia

Best proportionality between $|d_\infty|$ and λ

** λ_{MAX1} **
`diff[max(Dj(1:100)),Dj(5)]`/$\Delta_{samples}$

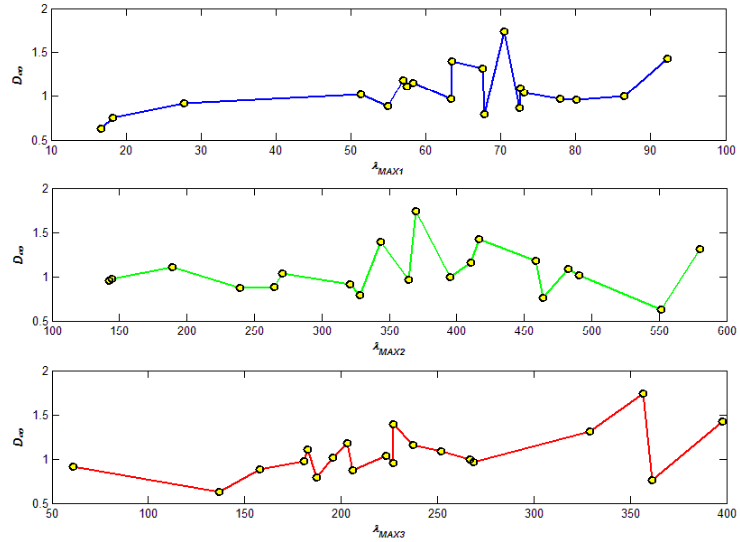
** λ_{MAX2} **
Type of fit:
Polynomial (9th degree)

** λ_{MAX3} **
Type of fit:
Custom Fit
$(d(t)=(d_0 d_\infty)/d_0+e^{-\lambda t}d_\infty)$

$$Potenza_2 = \frac{1}{M}\sum\frac{Amplitude_{ECG}}{T_s}$$

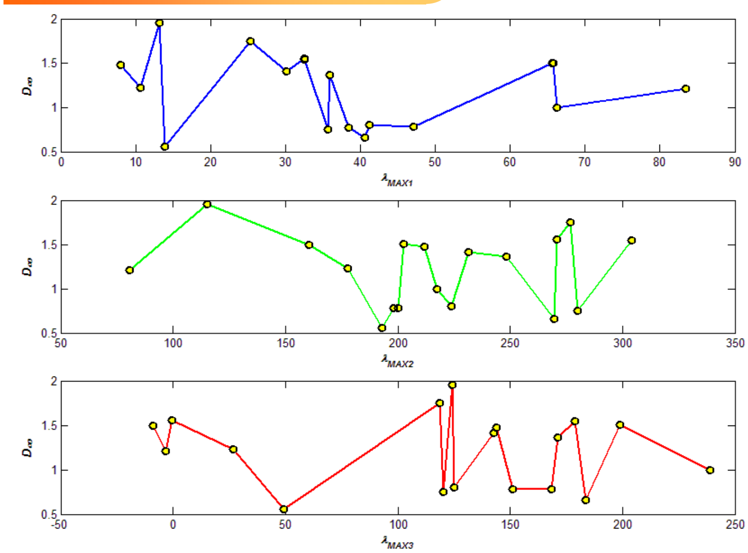
Results

d_∞ vs λ_{MAX} *(Patology: Normal)*



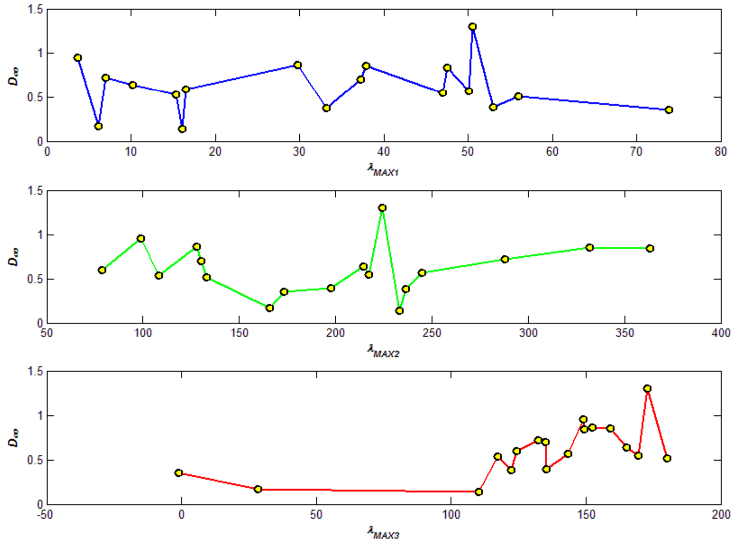
Results

d_∞ vs λ_{MAX} *(Patology: Arrhythmia)*



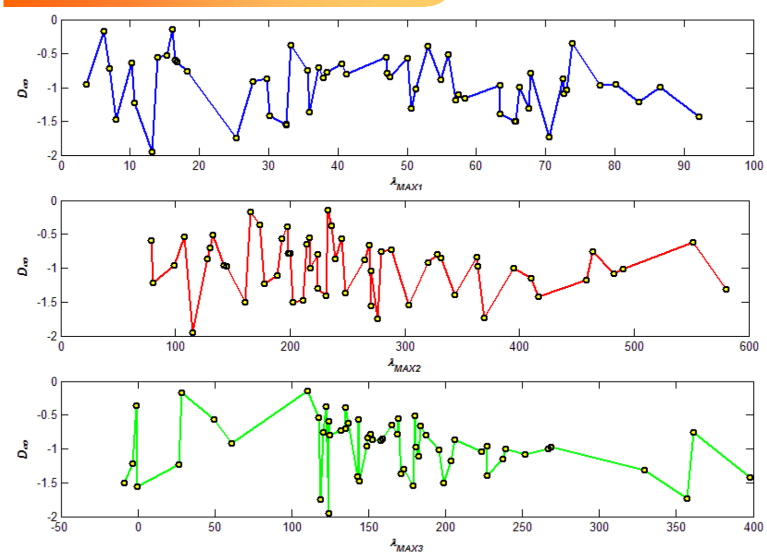
Results

d_∞ vs λ_{MAX} *(Patology: Ventr. Arrhythmia)*



Results

d_∞ vs λ_{MAX} *(All Patology)*



Future Development

1

Initial conditions obtained by *visual inspection* on the P-wave

Operator Dependent

Possible Solution

Neural Network for **P-wave recognition**

Automatic search of initial conditions

2

Algoritm of Automatic clustering for 3D graphics

Conclusions

The asymptotic distance between trajectories, d_∞, has been obtained from computation of d_j

dj trend is similar to one reported in literature on Chaotic System

The study of the d_∞ and the Lyapunov Exponent are performed simultaneously

Application

Theoretical study

Need more medical statistics and inputs!

Biomedical Application: Automatic Diagnostic

healthy

unhealthy

Algorithm for Decision Tree Induction

- Basic algorithm (a greedy algorithm)
  - Tree is constructed in a top-down recursive divide-and-conquer manner
  - At start, all the training examples are at the root
  - Attributes are categorical (if continuous-valued, they are discretized in advance)
  - Examples are partitioned recursively based on selected attributes
  - Test attributes are selected on the basis of a heuristic or statistical measure (e.g., information gain)
- Conditions for stopping partitioning
  - All samples for a given node belong to the same class
  - There are no remaining attributes for further partitioning – majority voting is employed for classifying the leaf
  - There are no samples left

Attribute Selection: Information Gain

- Select the attribute with the highest information gain
- Let p_i be the probability that an arbitrary tuple in D belongs to class C_i, estimated by $|C_{i,D}|/|D|$
- Expected information (entropy) needed to classify a tuple in D:

$$Info(D) = -\sum_{i=1}^{m} p_i \log_2(p_i)$$

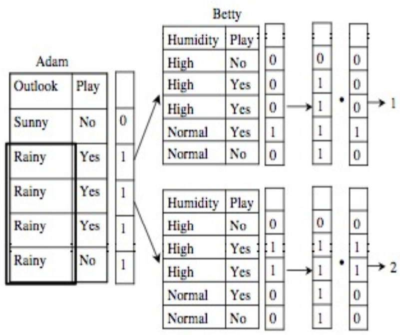
- Information needed (after using A to split D into v partitions) to classify D:

$$Info_A(D) = \sum_{j=1}^{v} \frac{|D_j|}{|D|} \times I(D_j)$$

- Information gained by branching on attribute A

$$Gain(A) = Info(D) - Info_A(D)$$

Distributed Decision Tree Construction



- Adam sends Betty "Outlook = Rainy"
- Betty constructs "Humidity=High & Play=Yes" and "Humidity=Normal & Play =Yes"
- Dot product represents tuples "Outlook = Rainy & Humidity = Normal & Play =Yes" AND "Outlook = Rainy & Humidity = High & Play =Yes"

Example Obtained from: C Gianella, K Liu, T Olsen and H Kargupta, "Communication efficient construction of decision trees over heterogeneously distributed data", ICDM 2004

PLANET: Parallel Learning for Assembling Numerous Ensemble Trees

- Ref: B Panda, J. S. Herbach, S. Basu, R. J. Bayardo, "PLANET: Massively Parallel Learning of Tree Ensembles with Map Reduce", VLDB 2009
- Components
  - Controller (maintains a ModelFile)
  - MapReduceQueue and InMemoryQueue

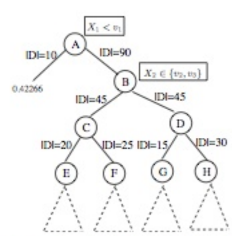
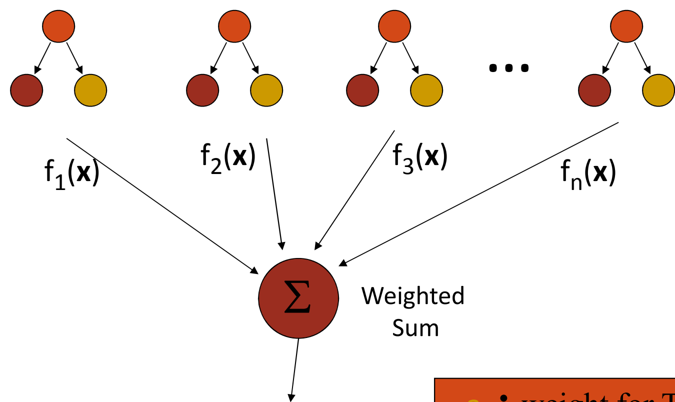


Figure 1: Example Tree. Note that the labels on the nodes (in boxes) are the split predicates, while the labels on the edges are the sizes of the dataset in each branch (|D| denotes the dataset size in that branch in this figure).

Classification Function of Ensemble Classifier



$f(x) = \sum_i a_i f_i(x)$

a_i : weight for Tree i

$f_i(x)$: classification of Tree i

The Distributed Boosting Algorithm

- k distributed sites storing homogeneously partitioned data
- At each local site, initialize the local distribution Δ_j
- Keep track of the global initial distribution by broadcasting Δ_j
- For each iteration across all sites
  - Draw indices from the local data set based of the global distribution
  - Train a weak learner and distribute to all sites
  - Create an ensemble by combining weak learners; use the ensemble to compute the weak hypothesis
  - Compute weights, and re-distribute to all sites
  - Update distribution and repeat until termination.
- Reference: A. Lazarevic and Z. Obradovic, "The Distributed Boosting Algorithm", KDD 2001.

Factor and Component Analysis

esp. Principal Component Analysis (PCA&ICA)

Why Factor or Component Analysis?

- We have too many observations and dimensions
  - To reason about or obtain insights from
  - To visualize
  - Too much noise in the data
  - Need to "reduce" them to a smaller set of factors
  - Better representation of data without losing much information
  - Can build more effective data analyses on the reduced-dimensional space: classification, clustering, pattern recognition
- Combinations of observed variables may be more effective bases for insights, even if physical meaning is obscure

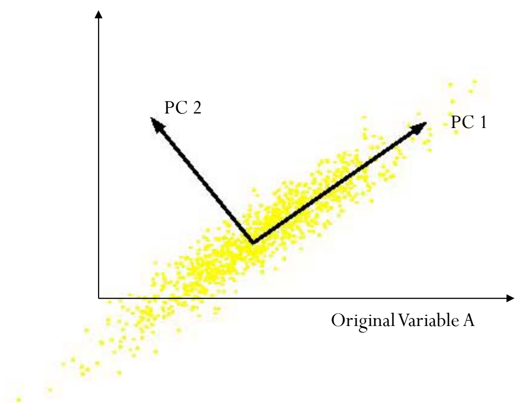
Basic Concept

- What if the dependences and correlations are not so strong or direct?
- And suppose you have 3 variables, or 4, or 5, or 10000?
- Look for the phenomena underlying the observed covariance/co-dependence in a set of variables
  - Once again, phenomena that are uncorrelated or independent, and especially those along which the data show high variance
- These phenomena are called "factors" or "principal components" or "independent components," depending on the methods used
  - Factor analysis: based on variance/covariance/correlation
  - Independent Component Analysis: based on independence

Principal Component Analysis

- Most common form of factor analysis
- The new variables/dimensions
  - Are linear combinations of the original ones
  - Are uncorrelated with one another
    - Orthogonal in original dimension space
  - Capture as much of the original variance in the data as possible
  - Are called Principal Components

What are the new axes?



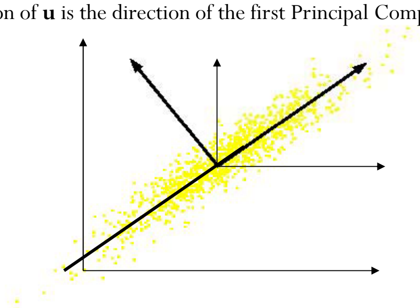
- Orthogonal directions of greatest variance in data
- Projections along PC1 discriminate the data most along any one axis

Principal Components

- First principal component is the direction of greatest variability (covariance) in the data
- Second is the next orthogonal (uncorrelated) direction of greatest variability
  - So first remove all the variability along the first component, and then find the next direction of greatest variability
- And so on …

Computing the Components

- Data points are vectors in a multidimensional space
- Projection of vector **x** onto an axis (dimension) **u** is **u.x**
- Direction of greatest variability is that in which the average square of the projection is greatest
  - I.e. **u** such that $E((\mathbf{u.x})^2)$ over all **x** is maximized
  - (we subtract the mean along each dimension, and center the original axis system at the centroid of all data points, for simplicity)
  - This direction of **u** is the direction of the first Principal Component



Computing the Components

- $E((\mathbf{u.x})^2) = E((\mathbf{u.x})(\mathbf{u.x})^T) = E(\mathbf{u.x.x}^T.\mathbf{u}^T)$
- The matrix $\mathbf{C} = \mathbf{x.x}^T$ contains the correlations (similarities) of the original axes based on how the data values project onto them
- So we are looking for w that maximizes $\mathbf{uCu}^T$, subject to **u** being unit-length
- It is maximized when w is the principal eigenvector of the matrix **C**, in which case
  - $\mathbf{uCu}^T = \mathbf{u}\lambda\mathbf{u}^T = \lambda$ if **u** is unit-length, where λ is the principal eigenvalue of the correlation matrix C
  - The eigenvalue denotes the amount of variability captured along that dimension

Why the Eigenvectors?

Maximise $\mathbf{u}^T\mathbf{x}\mathbf{x}^T\mathbf{u}$ s.t $\mathbf{u}^T\mathbf{u} = 1$

Construct Langrangian $\mathbf{u}^T\mathbf{x}\mathbf{x}^T\mathbf{u} - \lambda\mathbf{u}^T\mathbf{u}$

Vector of partial derivatives set to zero

$$\mathbf{x}\mathbf{x}^T\mathbf{u} - \lambda\mathbf{u} = (\mathbf{x}\mathbf{x}^T - \lambda\mathbf{I})\ \mathbf{u} = 0$$

As $\mathbf{u} \neq \mathbf{0}$ then $\mathbf{u}$ must be an eigenvector of $\mathbf{x}\mathbf{x}^T$ with eigenvalue λ

Singular Value Decomposition

The first root is called the prinicipal eigenvalue which has an associated orthonormal ($\mathbf{u}^T\mathbf{u} = 1$) *eigenvector* $\mathbf{u}$

Subsequent roots are ordered such that $\lambda_1 > \lambda_2 > \ldots > \lambda_M$ with rank($\mathbf{D}$) non-zero values.

Eigenvectors form an orthonormal basis i.e. $\mathbf{u}_i^T\mathbf{u}_j = \delta_{ij}$

The eigenvalue decomposition of $\mathbf{x}\mathbf{x}^T = \mathbf{U\Sigma U}^T$

where $\mathbf{U} = [\mathbf{u}_1, \mathbf{u}_2, \ldots, \mathbf{u}_M]$ and $\mathbf{\Sigma} = \text{diag}[\lambda_1, \lambda_2, \ldots, \lambda_M]$

Similarly the eigenvalue decomposition of $\mathbf{x}^T\mathbf{x} = \mathbf{V\Sigma V}^T$

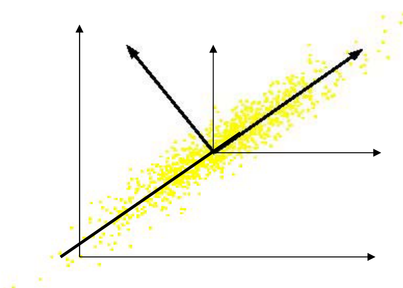
The SVD is closely related to the above $\mathbf{x} = \mathbf{U}\ \mathbf{\Sigma}^{1/2}\mathbf{V}^T$

The left eigenvectors $\mathbf{U}$**,** right eigenvectors $\mathbf{V}$**,**

singular values = square root of eigenvalues**.**

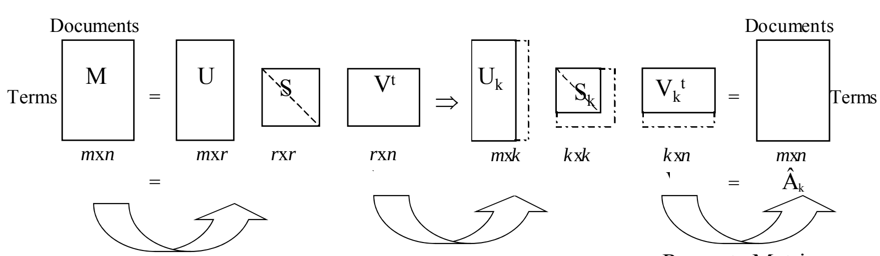
Computing the Components

- Similarly for the next axis, etc.
- So, the new axes are the eigenvectors of the matrix of correlations of the original variables, which captures the similarities of the original variables based on how data samples project to them



- Geometrically: centering followed by rotation
  - Linear transformation

Computing and Using LSI



Singular Value Decomposition (SVD): Convert term-document matrix into 3matrices U, S and V

Reduce Dimensionality: Throw out low-order rows and columns

Recreate Matrix: Multiply to produce approximate term-document matrix. Use new matrix to process queries OR, better, map query to reduced space

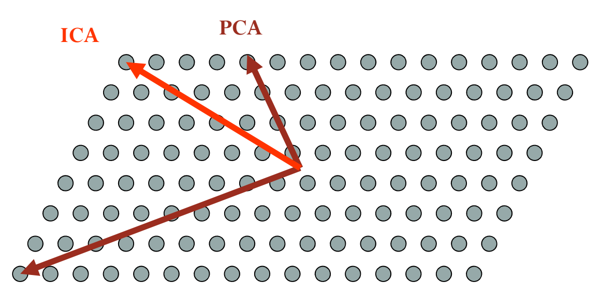
What LSI can do

- LSI analysis effectively does
  - Dimensionality reduction
  - Noise reduction
  - Exploitation of redundant data
  - Correlation analysis and Query expansion (with related words)
- Some of the individual effects can be achieved with simpler techniques (e.g. thesaurus construction). LSI does them together.
- LSI handles synonymy well, not so much polysemy
- Challenge: SVD is complex to compute ($O(n^3)$)
  - Needs to be updated as new documents are found/updated

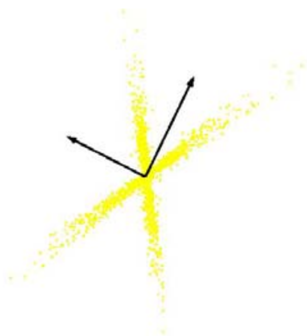
Limitations of PCA

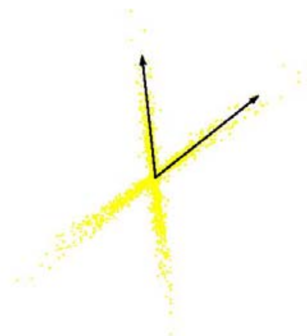
Should the goal be finding independent rather than pair-wise uncorrelated dimensions

•Independent Component Analysis (ICA)



PCA vs ICA





PCA
(orthogonal coordinate)

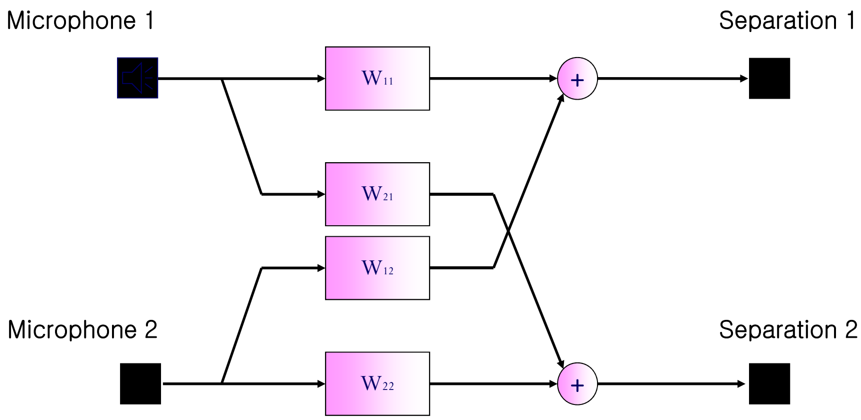
ICA
(non-orthogonal coordinate)

PCA applications -Eigenfaces

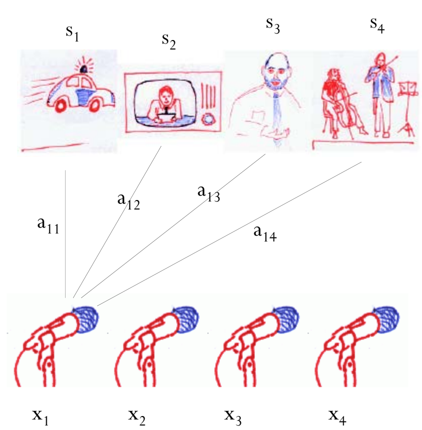
To generate a **set of eigenfaces:**

1. Large set of digitized images of human faces is taken under the same lighting conditions.
2. The images are normalized to line up the eyes and mouths.
3. The eigenvectors of the covariance matrix of the statistical distribution of face image vectors are then extracted.
4. These eigenvectors are called eigenfaces.

Source Separation Using ICA



The ICA model



$x_i(t) = a_{i1}*s_1(t) +$
$a_{i2}*s_2(t) +$
$a_{i3}*s_3(t) +$
$a_{i4}*s_4(t)$

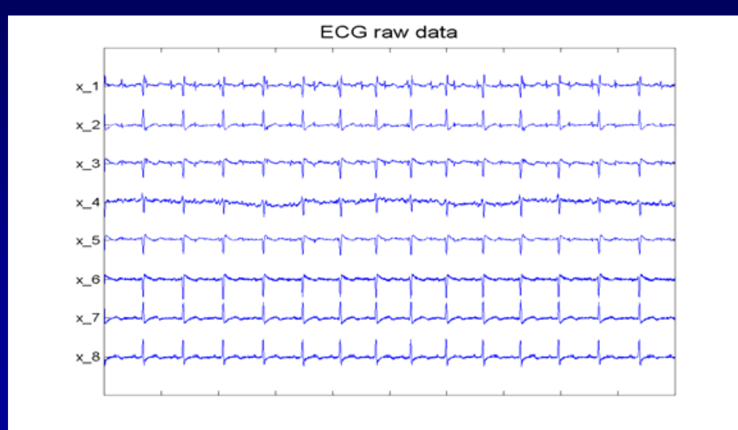
Here, i=1:4.

In vector-matrix notation, and dropping index t, this is
$\mathbf{x} = \mathbf{A} * \mathbf{s}$

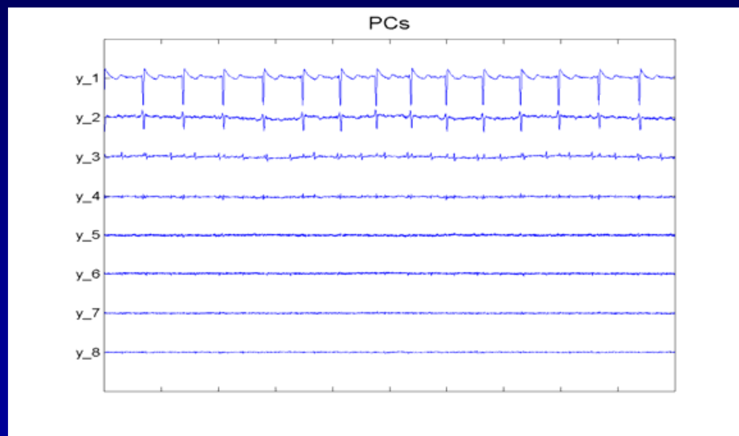
Application domains of ICA

- Blind source separation
- Image denoising
- Medical signal processing – fMRI, ECG, EEG
- Modelling of the hippocampus and visual cortex
- Feature extraction, face recognition
- Compression, redundancy reduction
- Watermarking
- Clustering
- Time series analysis (stock market, microarray data)
- Topic extraction
- Econometrics: Finding hidden factors in financial data

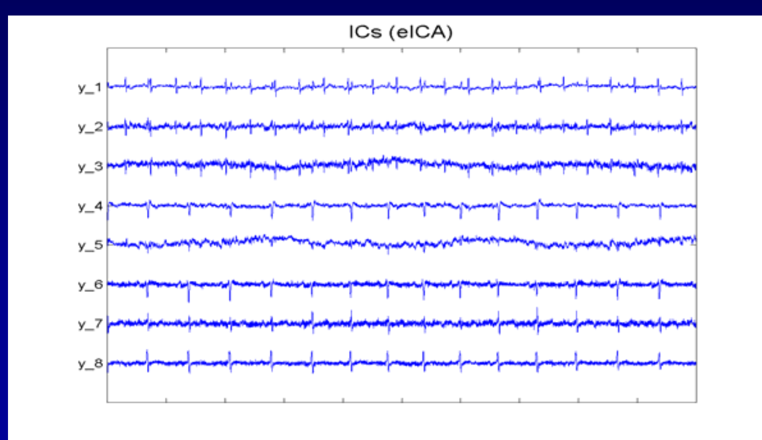
Feature Extraction in ECG data (Raw Data)



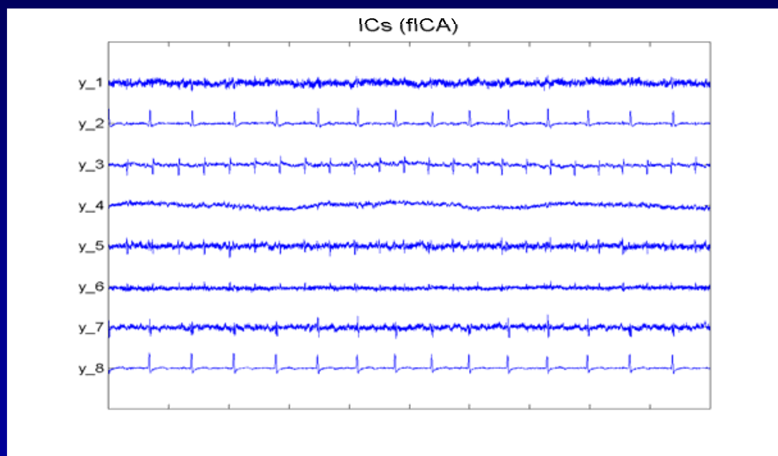
Feature Extraction in ECG data (PCA)



Feature Extraction in ECG data (Extended ICA)



Feature Extraction in ECG data (flexible ICA)



PCA vs ICA

- Linear Transform
  - Compression
  - Classification
- PCA
  - Focus on uncorrelated and Gaussian components
  - Second-order statistics
  - Orthogonal transformation
- ICA
  - Focus on independent and non-Gaussian components
  - Higher-order statistics
  - Non-orthogonal transformation

Gaussians and ICA

- If some components are gaussian and some are non-gaussian.
  - Can estimate all non-gaussian components
  - Linear combination of gaussian components can be estimated.
  - If only one gaussian component, model can be estimated
- ICA sometimes viewed as non-Gaussian factor analysis

Detection of Ischemic ST segment Deviation Episode in the ECG

Reflection of Ischemia in ECG:

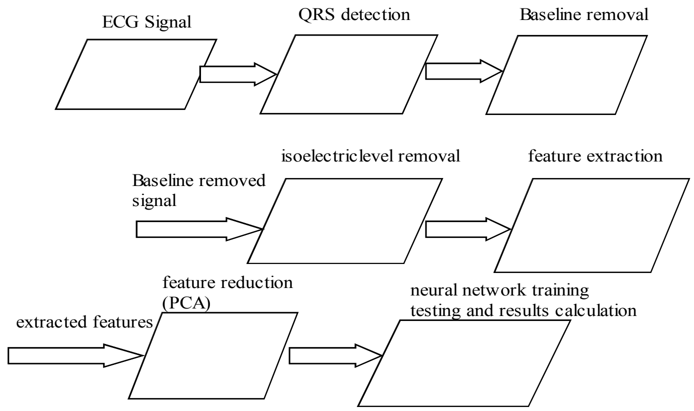
- ST segment deviation

i. Elevation

ii. Depression

- T wave Inversion

System Architecture



Detection of Ischemic ST segment Deviation Episode in the ECG

QRS detection

In order to proceed with ST deviation:

•QRS onset

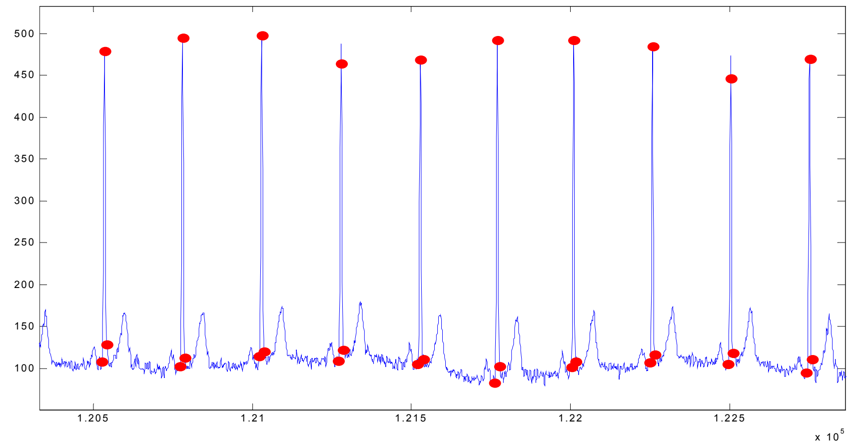
•QRS offset

•QRS fudicial point.

•DWT (discrete wavelet transform) based QRS detector .

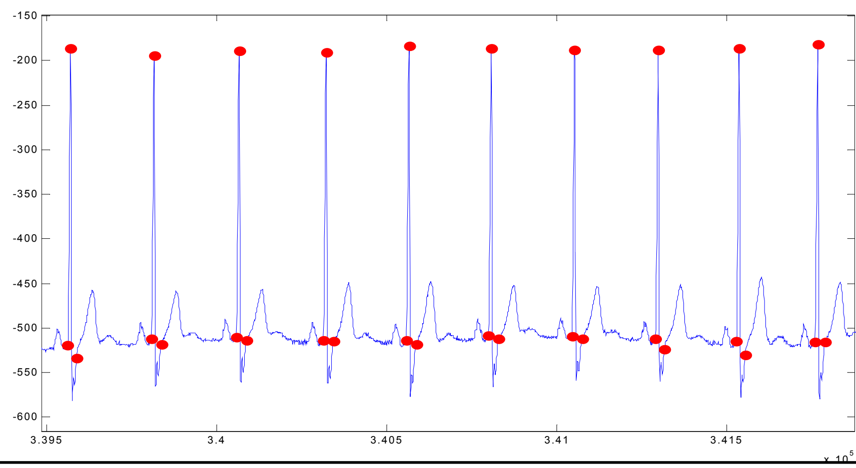
Detection of Ischemic ST segment Deviation Episode in the ECG

EDC Database Subject #e0103 QRS points



Detection of Ischemic ST segment Deviation Episode in the ECG

EDC Database Subject #e0509 QRS points



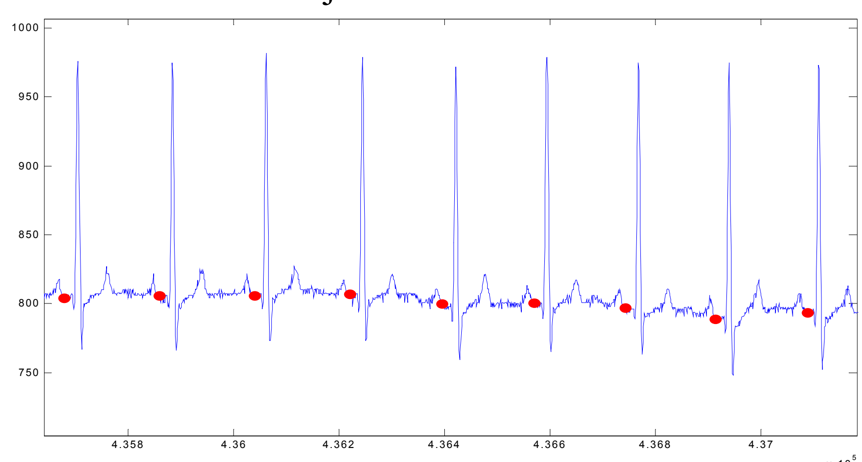
Detection of Ischemic ST segment Deviation Episode in the ECG

Isoelectric level:

- Flattest region on the signal
- Value equal or very close to zero.
- Region starts 80ms before the QRS on
- Ends at QRS on.

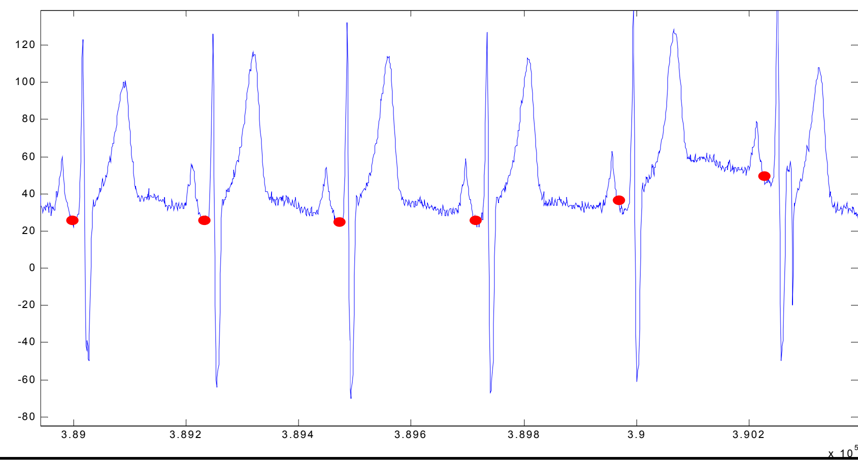
Detection of Ischemic ST segment Deviation Episode in the ECG

EDC Database Subject #e0515 Isoelectric level



Detection of Ischemic ST segment Deviation Episode in the ECG

EDC Database Subject #e1301 Isoelectric level



Detection of Ischemic ST segment Deviation Episode in the ECG

Feature extraction:

- •ST region refers as ROI (region of interest)
- •ROI (26 samples after the qrs_off)
- •Subtraction Isoelectric level from ROI
- •ST deviation

Detection of Ischemic ST segment Deviation Episode in the ECG

Feature Space:

- Size of the features is 26 X no. of beats of each subject
- Which is more time consuming when it comes to classify or train a neural network for it.

Detection of Ischemic ST segment Deviation Episode in the ECG

PCA(Principal component analysis):

Procedure:

1. Project the data as 1-dimensional Data sets
2. Subtract mean of the data from each data set
3. Combine the mean centered data sets (mean centered matrix)
4. Multiply the mean centered matrix by it's transpose (Covariance matrix)

Detection of Ischemic ST segment Deviation Episode in the ECG

PCA(Principal component analysis):

Procedure:

5. This covariance matrix has up to P eigenvectors associated with non-zero eigenvalues.
6. Assuming P<N. The eigenvectors are sorted high to low.
7. The eigenvector associated with the largest eigenvalue is the eigenvector that finds the greatest variance in the data.

Detection of Ischemic ST segment Deviation Episode in the ECG

PCA(Principal component analysis):

Procedure:

8. Smallest eigenvalue is associated with the eigenvector that finds the least variance in the data.
9. According to a threshold Variance, reduce the dimensions by discarding the eigenvectors with variance less than that threshold.

Detection of Ischemic ST segment Deviation Episode in the ECG

Training of MLIII Data

- Total beats: 184246
- Used for Training NN: 52493
- Used for Cross-validation: 20123
- Used for Testing: 110595

Detection of Ischemic ST segment Deviation Episode in the ECG

Training Results

Lead	Total Beats	Training Beats	Cross-Validation Beats	Cross-Validation Error
MLIII	73651	52493	20123	0.068%

Detection of Ischemic ST segment Deviation Episode in the ECG

Accuracy Parameters

TP (True Positives)

Target and predicted value both are positives.

FN (False Negative)

Target value is +ive and predicted one –ive.

FP (False Positive)

Target value is –ive and predicted one +ive.

TN (True Negative)

Target and predicted both are –ive.

Detection of Ischemic ST segment Deviation Episode in the ECG

Accuracy Parameters

Sensitivity

TP/(TP+FN)*100

Specificity

TN/(TN+FP)*100

Detection of Ischemic ST segment Deviation Episode in the ECG

MLIII Data

Lead	Total beats	Normal	Ischemic
MLIII	184246	174830	9416
Training	73651	68939	4712
Testing	110595	105891	4704

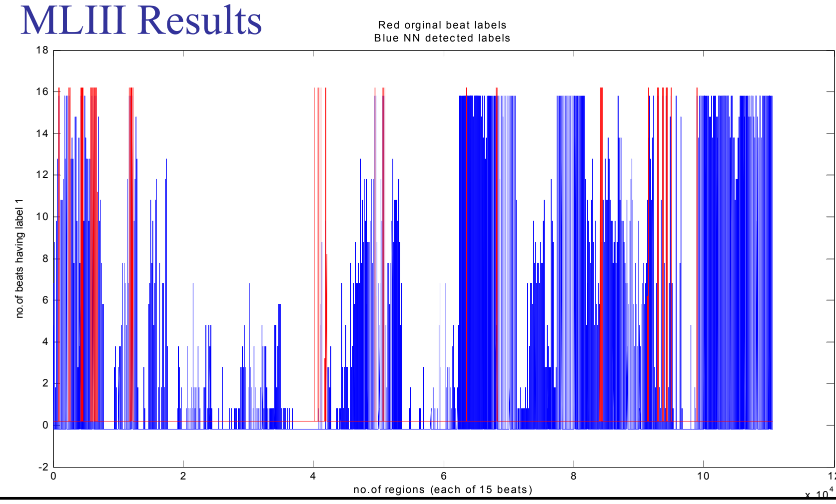
Detection of Ischemic ST segment Deviation Episode in the ECG

MLIII Testing Results

Lead	No.0f Beats	Sensiti vity	Specifi city	Thresh old
MLIII	110595	21%	99%	0
MLIII	110595	4%	99%	0.7
MLIII	110595	76%	72%	-0.7

Detection of Ischemic ST segment Deviation Episode in the ECG

MLIII Results



Application of the Discrete Wavelet transform in Beat Rate Detection

Outline

- Introduction to Wavelet Transform
- Applications of the Discrete Wavelet Transform in Beat Rate Detection
  - DWT Based Beat Rate Detection in ECG Analysis.
  - Improved ECG Signal Analysis Using Wavelet and Feature.
- Conclusion
- Reference

Introduction to wavelet transform

- Fourier transform is the well-known tool for signal processing. $X(f)=\int_{-\infty}^{\infty} x(t)e^{j2\pi ft}dt$
  - One limitation is that a Fourier transform can't deal effectively with non-stationary signal.
- Short time Fourier transform

$$X(t,f)=\int_{-\infty}^{\infty} w(t-\tau)x(\tau)e^{-j2\pi f\tau}d\tau \quad \text{where } w(t) \text{ is mask function}$$

Introduction to wavelet transform

- Gabor Transform
  - The mask function is satisfied with Gaussian distribution.
- Uncertainly principle

$$\sigma_t \sigma_f \geq \frac{1}{4\pi}$$

$$where \ \sigma_t^2 = \frac{\int t^2 |x(t)|^2 dt}{\int |x(t)|^2 dt}, \ \sigma_f^2 = \frac{\int f^2 |X(f)|^2 df}{\int |X(f)|^2 df}$$

- We expected to occur a high resolution in time domain, and then adjust σ_t^2 or σ_f^2.

16 9 /2 2

Introduction to wavelet transform

- The principle of wavelet transform is based on the concept of STFT and Uncertainly principle.
  - A mother wavelet $\psi(t)$.
  - Scaling $\frac{1}{\sqrt{a}}\psi(\frac{t}{a})$ and translating $\psi(t \pm b)$.
    - Sub-wavelets

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi(\frac{t-b}{a})$$

    - Fourier transform

$$\varphi(t) = F[\psi(t)]$$

$$\varphi_{a,b}(t) = F[\psi_{a,b}(t)]$$

17 0 /2 2

Introduction to wavelet transform

- Continuous wavelet transform(CWT)

$$w_{a,b} = \langle \psi_{a,b}, x(t) \rangle = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) \psi_{a,b}\left(\frac{t-b}{a}\right) dt$$

- ICWT

$$x(t) = \frac{1}{C_\psi} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} w_{a,b} \psi_{a,b}(t) \frac{dadb}{a^2}$$

$$where \quad C_\psi = \int_0^{\infty} \frac{|\varphi(w)|}{w} dw \quad and \quad \int_{-\infty}^{\infty} |\varphi(w)| dw < \infty$$

17 1 /2 2

Introduction to wavelet transform

- Discrete wavelet transform(DWT)
  - Sub-wavelets $w_{m,n} = \langle x(t), \psi_{m,n} \rangle = a_0^{m/2} \int f(t) \psi(a_0^m(t) - nb_0) dt$
- IDWT $\psi_{m,n}(t) = a_0^{m/2} \psi(a_0^m(t) - nb_0) \qquad m,n \in Z$

$$x(t) = \sum_m \sum_n w_{m,n} \psi_{m,n}(t)$$

17 2 /2 2

DWT applications for beat rate detection

- **DWT Based Beat Rate Detection in ECG Analysis**
  - **The purpose of this paper is to detect heart beat rate by the concept of discrete wavelet transform, which is suitable for the non stationary ECG signals as it has adeuate scale values and shifting in time.**

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3
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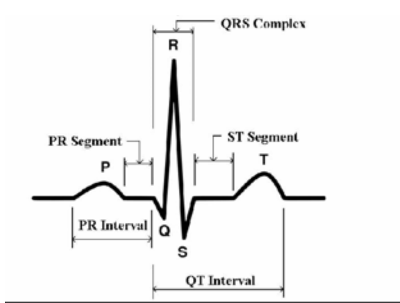
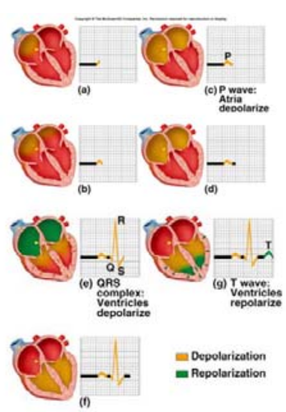
DWT Based Beat Rate Detection in ECG Analysis

- **ECG(Electrocardiogram) signal**





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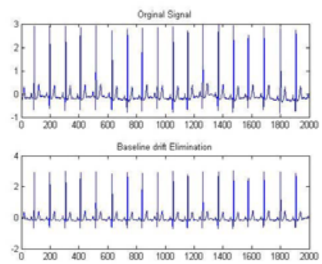
DWT Based Beat Rate Detection in ECG Analysis

- Preprocessing
  - Denoise
    - Baseline wandering



    - Moving aver ocedure.

17
5
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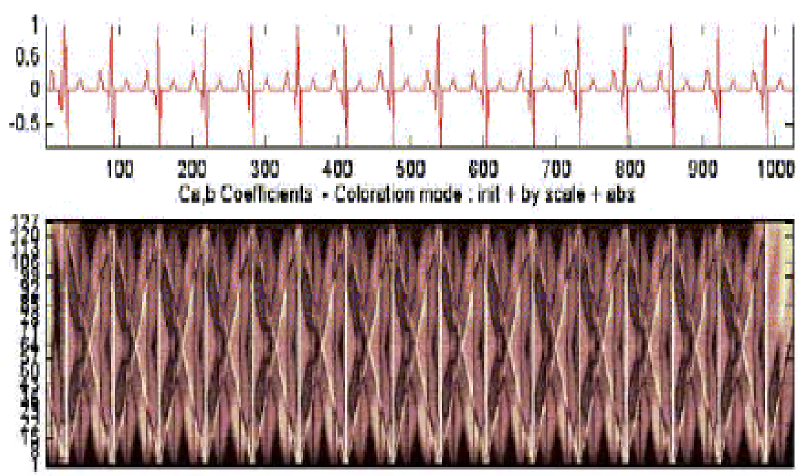
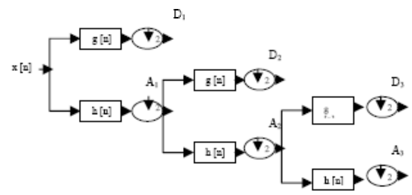
2

ECG signal [bottom] and the Wavelet transform [top]



DWT Based Beat Rate Detection in ECG Analysis

- Preprocessing
  - Denoising : The wavelet transform is used pre-filtering step for subsequent R spike detection by thresholding of the coefficients.
    - Decomposition.
    - Thresholding detail coefficients.
    - Reconstruction.



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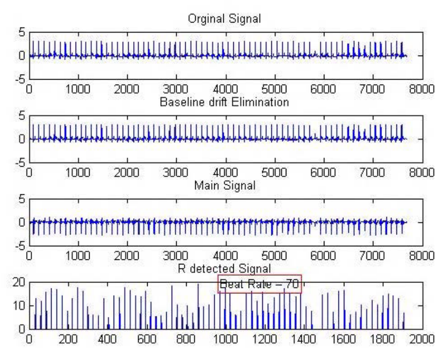
DWT Based Beat Rate Detection in ECG Analysis

- Feature extraction using DWT
  - Detect R-waves.
  - Thresholding.
    - Positive threshold.
    - Negative threshold.



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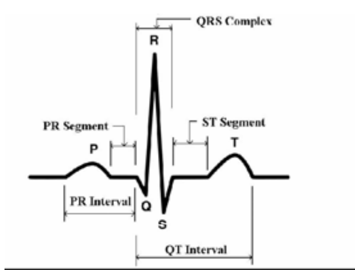
DWT applications for beat rate detection

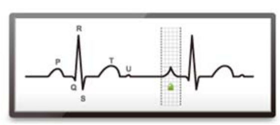
- **Improved ECG Signal Analysis Using Wavelet and Feature.**
  - **This paper introduced wavelet to extract features and then distinguish several heart beat condition, such as normal beats, atrial premature beats, and premature ventricular contractions.**

Improved ECG Signal Analysis Using Wavelet and Feature.

- Some kinds of ECG signal:



Normal beat

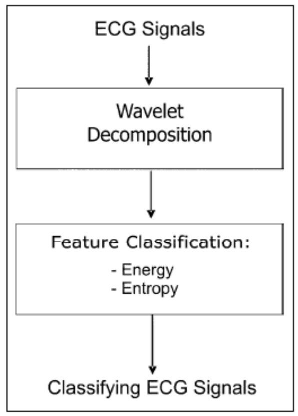


Atrial premature beat

Premature ventricular contractions

Improved ECG Signal Analysis Using Wavelet and Feature.

- **ECG signal analysis flow**



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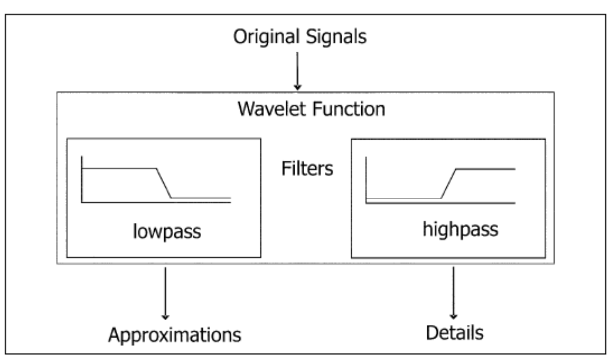
Improved ECG Signal Analysis Using Wavelet and Feature.

- **Feature Extraction**
  - **Matlab : wpdec function, the wavelet 'bior5.5'.**



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Improved ECG Signal Analysis Using Wavelet and Feature.

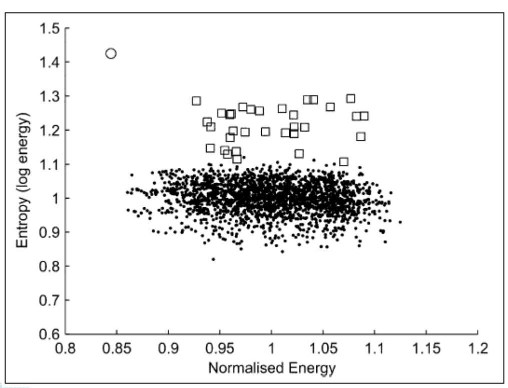
- **Feature Extraction**
  - **Energy**
  - **Normal Energy** $$E(j)_n = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - m)^2$$
  - **Entorpy** $$E(j)norm\_n = \frac{E(j)_n}{\sqrt{E(j)_1^2 + E(j)_2^2 + \cdots + E(j)_n^2}}$$

$$Ent(j)_{\log\_n} = \sum_{i=1}^{N}\log(x_i^2)$$

18 3 /2 2

Improved ECG Signal Analysis Using Wavelet and Feature.

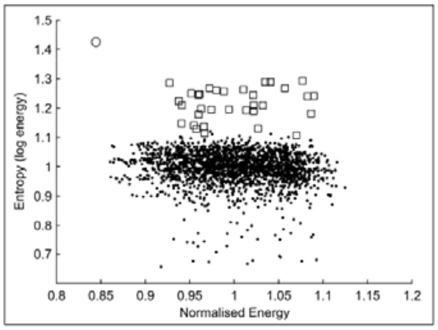
- **Feature Extraction**
  - **Clustering**

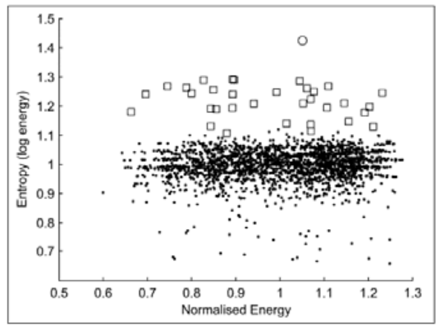


18 4 /2 2

Improved ECG Signal Analysis Using Wavelet and Feature.

- **Method 1**





wavelet: bior5.5, decomposition level: 1 and 3 with Method 1(●: normal beats, □: atrial premature beats, ○ : premature ventricular contractions)

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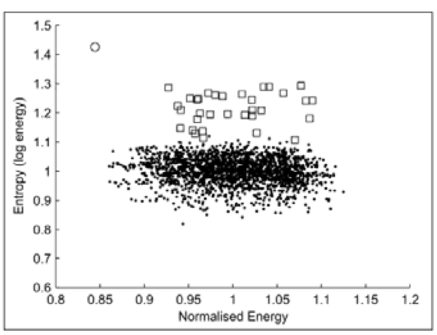
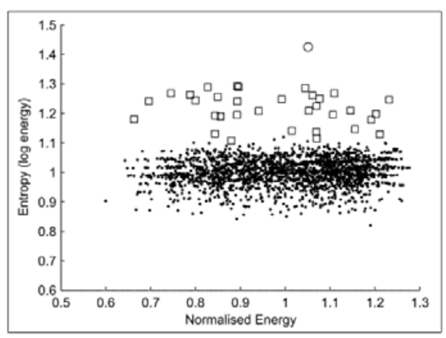
Improved ECG Signal Analysis Using Wavelet and Feature.

- **Method 2**





wavelet: bior5.5, decomposition level: 1 and 3 with Method 2(●: normal beats, □: atrial premature beats, ○ : premature ventricular contractions)

18/6/22

Conclusion

- Wavelet analysis is widely used in many application. Because it provides both time and frequency information, can overcome the limitation of Fourier transform.
- We can learn about the wavelet transform which is able to detect beat rate of signals and to classify the difference of signals.
- We also use the wavelet transform on the other beat rate detection.

18
7
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2

References

[1] Understanding 12 Lead EKGs ,A Practical Approach, BRADY: Understanding 12 Lead EKGS Ch. 14

[2] Data Mining and Medical Informatics , R. E. Abdel-Aal,November 2005

[3] Factor and Component Analysis, esp. Principal Component Analysis (PCA)

[4] Algorithms for Distributed Supervised and Unsupervised Learning, Haimonti Dutta
The Center for Computational Learning Systems (CCLS),Columbia University, New York.

[5]Applications of the DWT in beat rate detection, Ding jian,Jun, DISP lab, NTU

References

[6] Kyriacou, E.; Pattichis, C.; Pattichis, M.; Jossif, A.; Paraskevas, L.; Konstantinides, A.; Vogiatzis, D.; An m-Health Monitoring System for Children with Suspected Arrhythmias, 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2007 Page(s): 1794 - 1797

[7] Wang Zhiyu; Based on physiology parameters to design lie detector, International Conference on Computer Application and System Modeling (ICCASM), 2010 Page(s): V8-634 - V8-637

[8] Cutcutache, I.; Dang, T.T.N.; Leong, W.K.; Shanshan Liu; Nguyen, K.D.; Phan, L.T.X.; Sim, E.; Zhenxin Sun; Tok, T.B.; Lin Xu; Tay, F.E.H.; Weng-Fai Wong; BSN Simulator: Optimizing Application Using System Level Simulation, Sixth International Workshop on Wearable and Implantable Body Sensor Networks, 2009 Page(s): 9 - 14

[9] Chareonsak, C.; Farook Sana; Yu Wei; Xiong Bing; Design of FPGA hardware for a real-time blind source separation of fetal ECG signals, IEEE International Workshop on Biomedical Circuits and Systems, 2004 Page(s): S2/4 - 13-16

References

[10] Galeottei, L.; Paoletti, M.; Marchesi, C.; *Development of a low cost wearable prototype for long-term vital signs monitoring based on embedded integrated wireless module*, Computers in Cardiology, 2008 Page(s): 905 - 908

[11] Low, Y.F.; Mustaffa, I.B.; Saad, N.B.M.; Bin Hamidon, A.H.; *Development of PC-Based ECG Monitoring System*, 4th Student Conference on Research and Development, 2006 Page(s): 66 - 69

[12] Kyriacou, E.; Pattichis, C.; Hoplaros, D.; Jossif, A.; Kounoudes, A.; Milis, M.; Vogiatzis, D.; *Integrated platform for continuous monitoring of children with suspected cardiac arrhythmias*, 9th International Conference on Information Technology and Applications in Biomedicine, 2009 Page(s): 1 - 4

[13] Romero, I.; Grundlehner, B.; Penders, J.; Huisken, J.; Yassin, Y.H.; *Low-power robust beat detection in ambulatory cardiac monitoring*, IEEE Biomedical Circuits and Systems Conference, 2009 Page(s): 249 - 252

[14] Saeed, A.; Faezipour, M.; Nourani, M.; Tamil, L.; *Plug-and-play sensor node for body area networks*, IEEE/NIH Life Science Systems and Applications Workshop, 2009 Page(s): 104 - 107