Advanced Cases for ECG Signal Processing

ECE, UA

Advanced Case (1)

- A Classification Tree Approach for Cardiac Ischemia Detection Using Spatiotemporal Information From Three Standard ECG Leads

IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL. 58, NO. 1, JANUARY 2011

Content

Introduction

- ECG is the main information for diagnosis of the cardiac ischemia
- Decision-support approach: new classification tree (T-3C)
- Using Spatiotemporal Information
- Performance Comparison

Introduction

- 3-Lead acquisition system:
  - *easy to set up in self-care*
  - *not much sensitive to movement noise*
  - *retrieve the spatiotemporal information*
  - *sufficient for the reconstruction of a standard 12-lead ECG*
- Comparative analysis of electro-vectorcardiograms and their interpretation with auto-reference to the patient (CAVIAR)

Methods

A. Study Population Datasets

Data set	Diagnosis class	Number of cases	% of cases with a					% of Males
			LAD occlusion	LCX occlusion	LM occlusion	RCA occlusion	Prior MI [a]	
A	C	39	28	23	3	46	38	69
	I	45	24	22	2	51	31	56
B	C	51	39	12	2	47	29	55
	I	45	44	11	2	42	36	67

B. ECG Analysis and Measurements Computation Methods

- leads I, II, and V2
- Lyon program
- QMQD, ST60, Tmax, OCR, OCI

Methods

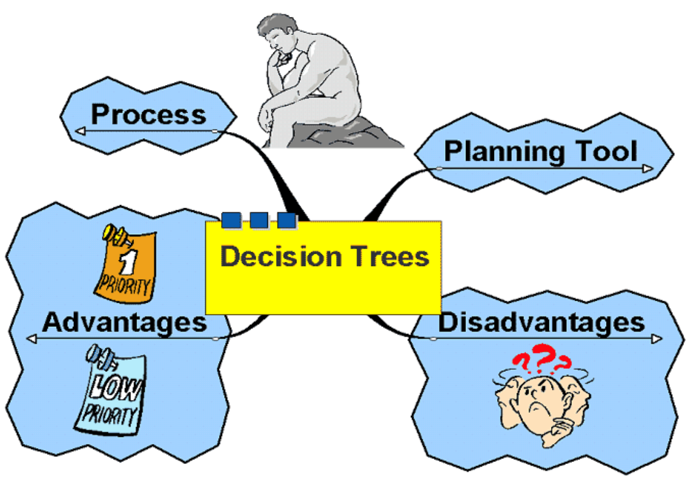
C. Decision-Making Methods

- *Classical Discriminant Analysis and Classification Tree*
  - BioMeDical statistical Package (BMDP)
  - CHAID, QUEST, C&RT, SPSS
- *New Classification Tree Method*
  - T-3C , learn to update the condition and threshold

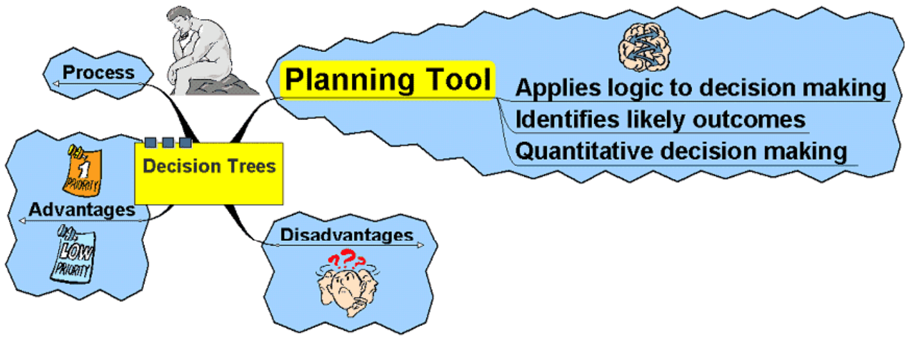
$$\text{If } (Vi \geq \text{Max}_C(Vi)), \text{ then class} = \text{I}$$

$$\text{If } (Vi < \text{Min}_I(Vi)), \text{ then class} = \text{C}.$$

Decision Trees



Planning Tool



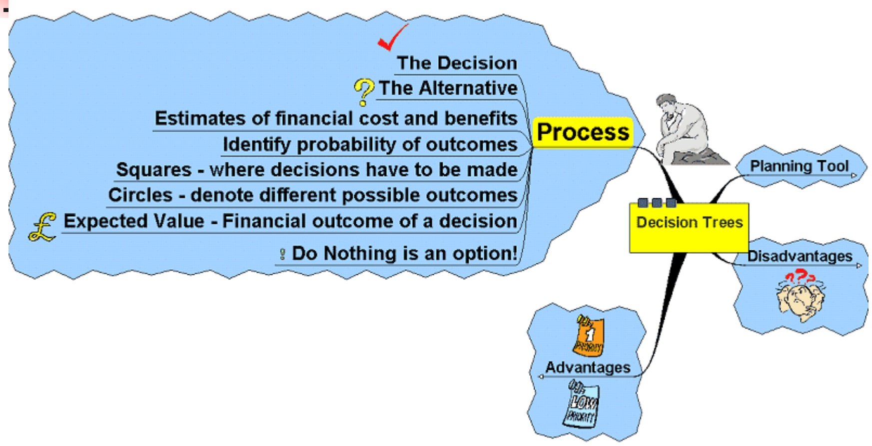
Decision Trees

- Enable a business to quantify decision making
- Useful when the outcomes are uncertain
- Places a numerical value on likely or potential outcomes
- Allows comparison of different possible decisions to be made

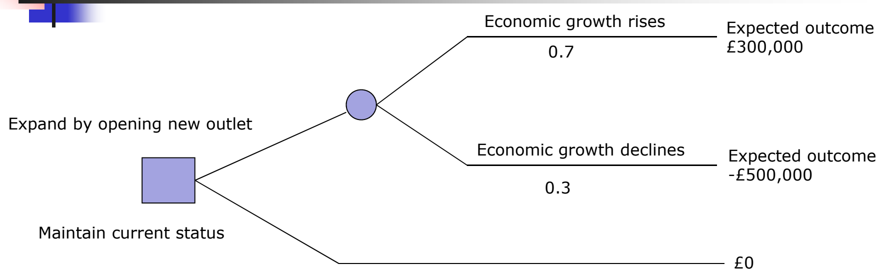
Decision Trees

- **Limitations:**
  - How accurate is the data used in the construction of the tree?
  - How reliable are the estimates of the probabilities?
  - Data may be historical – does this data relate to real time?
  - Necessity of factoring in the qualitative factors – human resources, motivation, reaction, relations with suppliers and other stakeholders

Process



The Process



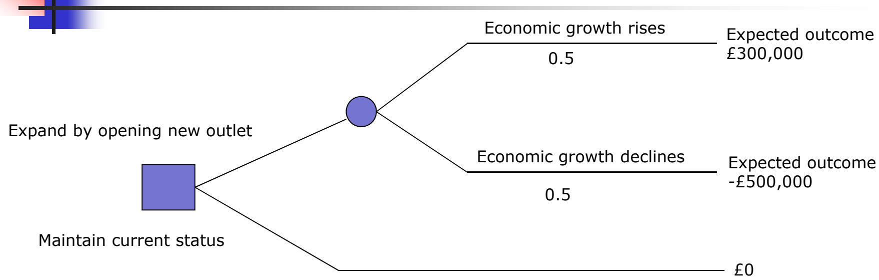
The circle denotes the point where different outcomes could occur. The estimates of the probability and the knowledge of the expected outcome allow the firm to make a calculation of the likely return. In this example it is:

Economic growth rises: 0.7 x £300,000 = £210,000

Economic growth declines: 0.3 x £500,000 = -£150,000

The calculation would suggest it is wise to go ahead with the decision (a net 'benefit' figure of +£60,000)

The Process



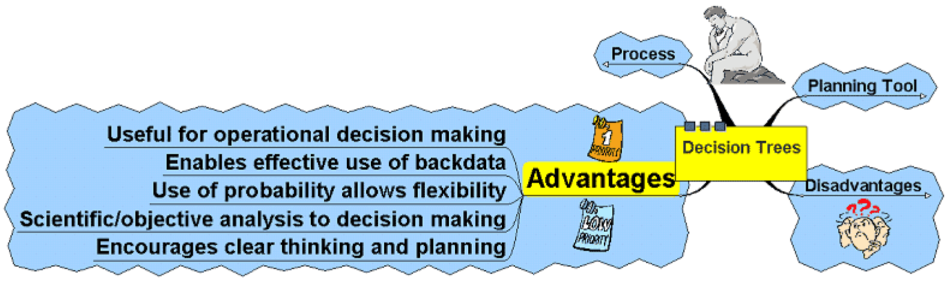
Look what happens however if the probabilities change. If the firm is unsure of the potential for growth, it might estimate it at 50:50. In this case the outcomes will be:

Economic growth rises: 0.5 x £300,000 = £150,000

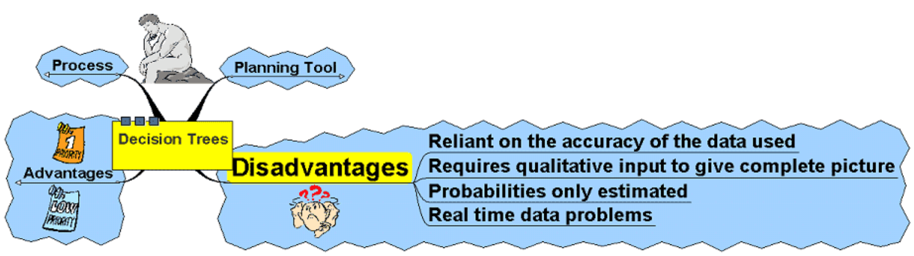
Economic growth declines: 0.5 x -£500,000 = -£250,000

In this instance, the net benefit is -£100,000 – the decision looks less favourable!

Advantages



Disadvantages



Results

	12-lead ECG measurements						3-lead ECG measurements								
	Discriminant analysis	Classification trees					Discriminant analysis		Classification trees						
	12-L ECG criteria	Chaid	Exhaustive Chaid	C&RT	Quest	T-3C	12-L ECG criteria	3-L ECG criteria	Chaid	Exhaustive Chaid	C&RT	Quest	Quest [c]	T-3C
Se	97.8 [a]	97.8	91.1	95.6	100	97.8	97.8 [b]	97.8	95.6	100	93.3	95.6	95.6	97.8
Sp	96.1 [a]	92.2	92.2	92.2	84.3	94.1	88.2 [b]	96.1	86.3	88.2	94.1	86.3	92.2	98.0
Acc	96.9 [a]	94.8	91.7	93.8	91.7	95.8	92.7 [b]	96.9	90.6	93.8	93.8	90.6	93.8	97.9

Discussion

- It is still possible to increase the diagnostic accuracy
- 3 orthogonal leads I, II, and V2 can bring more relevant information than 12-lead
- do not always yield for optimum results, T3C is easy to be implemented
- The number of classification steps for obtaining the best result specific to each method is rather smaller with the T-3C algorithm than with the others.

Conclusion

- New T3C approach for building a reliable decision tree
- Assessed for 3-lead and 12-lead measurement in different methods
- Four electrodes, easy and convenient to place and minimizing the signal noise.

Advanced Case (2)

- **Discrimination Power of Short-Term Heart Rate Variability Measures for CHF Assessment**
- IEEE TRANSACTIONS ON INFORMATION TECHNOLOGY IN BIOMEDICINE, VOL. 15, NO. 1, JANUARY 2011

Content

- Abstract
- Introduction
- Methods
- Results
- Conclusion

Abstract

- Investigate the discrimination power of short-term HRV for CHF.
- Sufficient real data extracted from public database.
- Time and frequency feature analysis
- CART discrimination method
- RMSSD, total power, high-frequencies power, LF/HF.

Introduction

- HRV is widely studied in patients suffering from chronic heart failure (CHF) but not the diagnosis.
- New York Heart Association (NYHA) classification.
- ECG has low sensitivity and specificity.
- Investigate the power of short-term HRV features in classifying CHF patients by CART.

Introduction

- CART
  - Fully understandable without advanced mathematical skills
  - Easy for clinical interpretation
  - Requires no assumptions regarding the underlying distribution of features' values
  - Iteratively splits the dataset, according to a criterion that maximizes the separation of the data

Methods

A. Data
- RR intervals extracted from 24-h ECG-Holter of patients
- Classified to NYHA I,II,III.
- Standard RR interval records

B. Short-term HRV measurement
- International Guidelines
- PhysioNet's HRV Toolkit
- power spectral density (PSD)
- normal-to-normal (NN) intervals
- ΔAVNN and ΔLF/HF

SELECTED HRV FEATURES

Measure	Description	Unit
AVNN	Average of all NN intervals	ms
SDNN	Standard deviation of all NN intervals.	ms
RMSSD	The square root of the mean of the sum of the squares of differences between adjacent NN intervals	ms
pNN50	Percentage of differences between adjacent NN intervals that are > 50 ms	%
TOTPWR	Total spectral power of all NN intervals 0-0.4 Hz.	ms^2
VLF	Total spectral power of all NN intervals 0-0.04 Hz	ms^2
LF	Total spectral power of all NN intervals 0.04-0.15 Hz	ms^2
HF	Total spectral power of all NN intervals 0.15-0.4 Hz	ms^2
LF/HF	Ratio of low to high frequency power	

What is CART?

- Classification And Regression Trees
- Developed by Breiman, Friedman, Olshen, Stone in early 80's.
  - Introduced tree-based modeling into the statistical mainstream
  - Rigorous approach involving cross-validation to select the optimal tree
- One of many tree-based modeling techniques.
  - CART -- the classic
  - CHAID
  - C5.0
  - Software package variants (SAS, S-Plus, R…)
  - Note: the "rpart" package in "R" is freely available

The Key Idea

Recursive Partitioning

- Take all of your data.
- Consider *all* possible values of *all* variables.
- Select the variable/value **(X=t_1)** that produces the greatest "separation" in the target.
  - **(X=t_1)** is called a "split".
- If $X < t_1$ then send the data to the "left"; otherwise, send data point to the "right".
- Now repeat same process on these two "nodes"
  - You get a "tree"
  - Note: CART only uses *binary* splits.

Let's Get Rolling

- Suppose you have 3 variables:

  # vehicles: {1,2,3…10⁺}
  Age category: {1,2,3…6}
  Liability-only: {0,1}

- At each iteration, CART tests all 15 splits.

  (#veh<2), (#veh<3),…, (#veh<10)
  (age<2),…, (age<6)
  (lia<1)

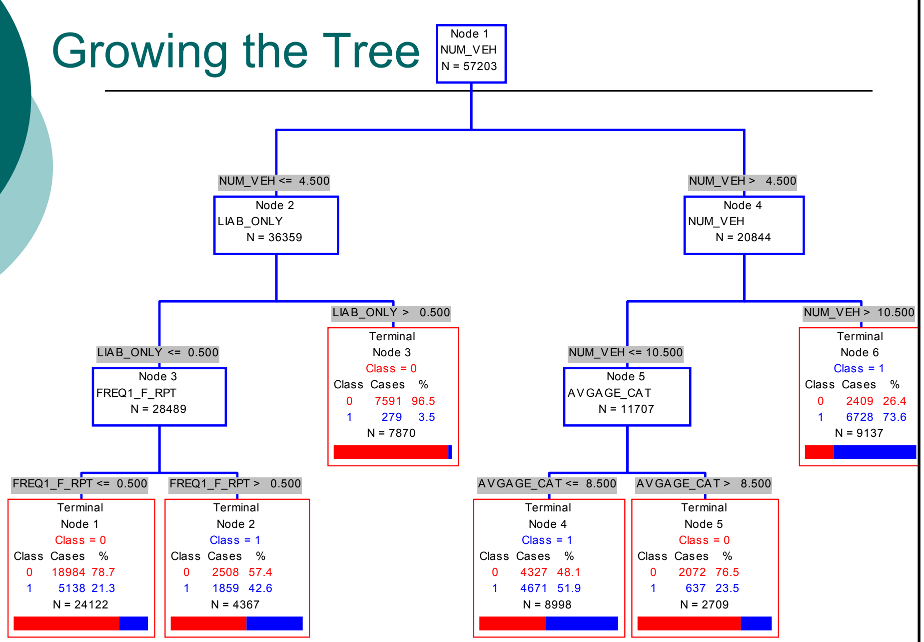
Select split resulting in greatest increase in *purity*.

- Perfect purity: each split has either all claims or all no-claims.
- Perfect impurity: each split has same proportion of claims as overall population.

Classification Tree Example: predict likelihood of a claim

- Commercial Auto Dataset
  - 57,000 policies
  - **34%** claim frequency
- Classification Tree using Gini splitting rule
- First split:
  - Policies with ≥5 vehicles have **58%** claim frequency
  - Else **20%**
  - Big increase in purity

Growing the Tree



Observations (Shaking the Tree)

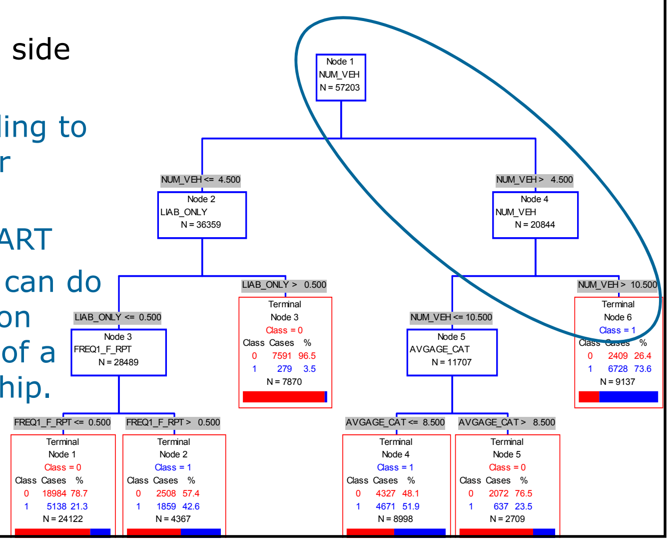
- First split (# vehicles) is rather obvious
  - More exposure ➔ more claims
- But it confirms that CART is doing something reasonable.
  - Also: the choice of splitting value 5 (not 4 or 6) is non-obvious.
  - This suggests a way of optimally "binning" continuous variables into a small number of groups

CART and Linear Structure

Notice Right-hand side of the tree...

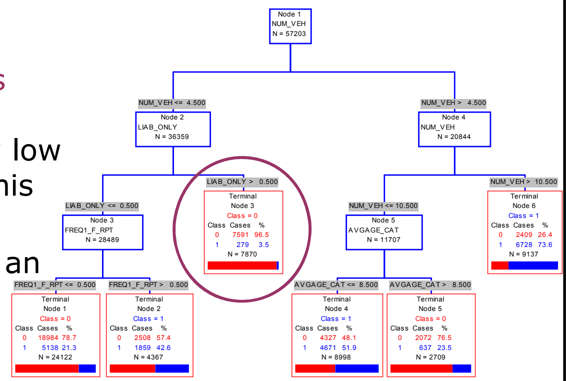
CART is struggling to capture a linear relationship

- Weakness of CART
- The best CART can do is a step function approximation of a linear relationship.



Interactions and Rules

- This tree is obviously not the best way to model this dataset.
- But notice node #3
- Liability-only policies with fewer than 5 vehicles have a very low claim frequency in this data.
  - Could be used as an underwriting rule
  - Or an interaction term in a GLM



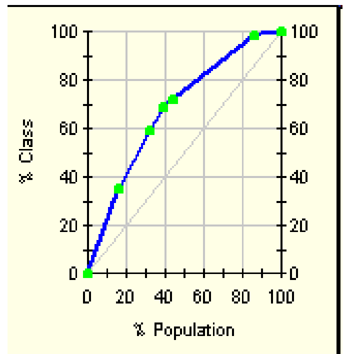
High-Dimensional Predictors

- *Categorical predictors*: CART considers every possible *subset* of categories
  - Nice feature
  - Very handy way to group massively categorical predictors into a small # of groups
- Left (fewer claims): dump, farm, no truck
- Right (more claims): contractor, hauling, food delivery, special delivery, waste, other

Gains Chart: Measuring Success

From left to right:

- Node 6: 16% of policies, 35% of claims.
- Node 4: add'l 16% of policies, 24% of claims.
- Node 2: add'l 8% of policies, 10% of claims.
- ..etc.
  - The steeper the gains chart, the stronger the model.
  - Analogous to a lift curve.
  - Desirable to use out-of-sample data.



Splitting Rules

- Select the variable value ($X=t_1$) that produces the greatest "separation" in the target variable.
- "Separation" defined in many ways.
  - Regression Trees (continuous target): use sum of squared errors.
  - Classification Trees (categorical target): choice of *entropy*, *Gini measure*, "*twoing*" splitting rule.

Regression Trees

- Tree-based modeling for ***continuous* target variable**
  - most intuitively appropriate method for loss ratio analysis
- Find split that produces greatest separation in

$$\Sigma[y - E(y)]^2$$

- i.e.: find nodes with minimal *within variance*
  - and therefore greatest *between variance*
  - like credibility theory
- Every record in a node is assigned the same yhat
  - ➔ model is a *step function*

Classification Trees

- Tree-based modeling for ***discrete* target variable**
- In contrast with regression trees, various measures of *purity* are used
- Common measures of purity:
  - Gini, entropy, "twoing"
- Intuition: an ideal retention model would produce nodes that contain either defectors only or non-defectors only
  - completely pure nodes

More on Splitting Criteria

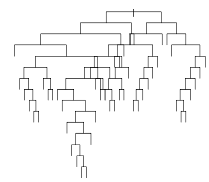
- Gini purity of a node **$p(1-p)$**
  - where p = relative frequency of defectors
- Entropy of a node **$-\Sigma p \log p$**
  - $-[p*\log(p) + (1-p)*\log(1-p)]$
  - Max entropy/Gini when p=.5
  - Min entropy/Gini when p=0 or 1
- Gini might produce *small* but pure nodes
- The "twoing" rule strikes a balance between *purity* and creating roughly *equal-sized nodes*
  - *Note: "twoing" is available in Salford Systems' CART but not in the "rpart" package in R.*

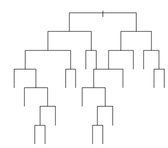
How CART Selects the Optimal Tree

- Use **cross-validation** (CV) to select the optimal decision tree.
- Built into the CART algorithm.
  - Essential to the method; not an add-on
- Basic idea: "grow the tree" out as far as you can…. Then "prune back".
- CV: tells you when to stop pruning.

Growing & Pruning

- One approach: stop growing the tree early.
  - But how do you know when to stop?
- CART: just grow the tree all the way out; then prune back.
  - Sequentially collapse nodes that result in the smallest change in purity.
  - "weakest link" pruning.



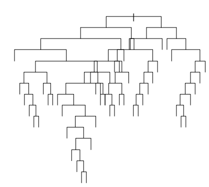


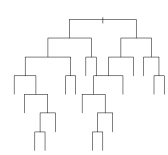
Finding the Right Tree

- "Inside every big tree is a small, perfect tree waiting to come out."

  --Dan Steinberg

  2004 CAS P.M. Seminar
- The optimal tradeoff of bias and variance.
- But how to find it??





Cost-Complexity Pruning

- Definition: Cost-Complexity Criterion

  $$R_\alpha = MC + \alpha L$$

  - MC = misclassification rate
    - Relative to # misclassifications in root node.
  - L = # leaves (terminal nodes)
  - You get a credit for lower MC.
  - But you *also* get a penalty for more leaves.
- Let T_0 be the biggest tree.
- Find sub-tree of T_α of T_0 that minimizes R_α.
  - Optimal trade-off of accuracy and complexity.

Weakest-Link Pruning

- Let's sequentially collapse nodes that result in the smallest change in purity.
- This gives us a nested sequence of trees that are all sub-trees of T_0.

  $$T_0 \gg T_1 \gg T_2 \gg T_3 \gg \dots \gg T_k \gg \dots$$

- Theorem: the sub-tree T_α of T_0 that minimizes R_α <u>is in this sequence</u>!
  - Gives us a simple strategy for finding best tree.
  - Find the tree in the above sequence that minimizes CV misclassification rate.

What is the Optimal Size?

- Note that α is a free parameter in:

$$R_\alpha = MC + \alpha L$$

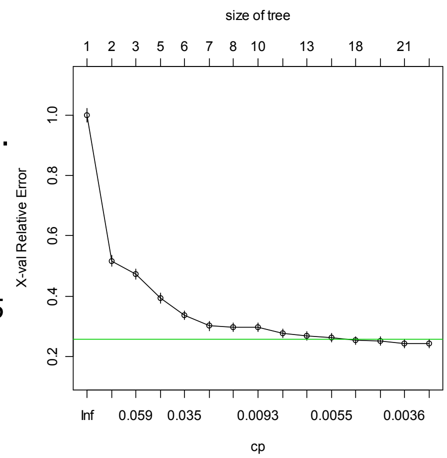
- 1:1 correspondence betw. α and size of tree.
- What value of α should we choose?
  - α=0 ➔ maximum tree T_0 is best.
  - α=big ➔ You never get past the root node.
  - Truth lies in the middle.
- Use cross-validation to select optimal α (size)

How to Cross-Validate

- Grow the tree on all the data: T_0.
- Now break the data into 10 equal-size pieces.
- 10 times: grow a tree on 90% of the data.
  - Drop the remaining 10% (test data) down the nested trees corresponding to each value of α.
  - For each α add up errors in all 10 of the test data sets.
- Keep track of the α corresponding to lowest test error.
- This corresponds to one of the nested trees $T_k \ll T_0$.

Just Right

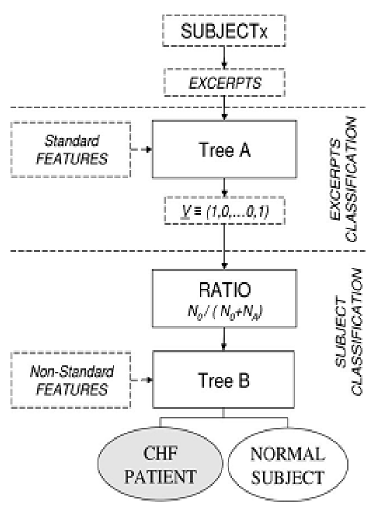
- Relative error: proportion of CV-test cases misclassified.
- According to CV, the 15-node tree is nearly optimal.
  - In summary: grow the tree all the way out.
  - Then weakest-link prune back to the 15 node tree.



Methods

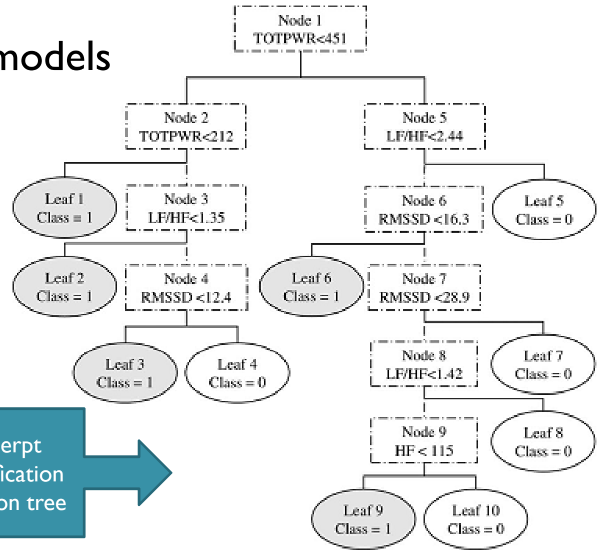
C. Classification

- 1) Excerpts Classification
- 2) Subject Classification



Methods

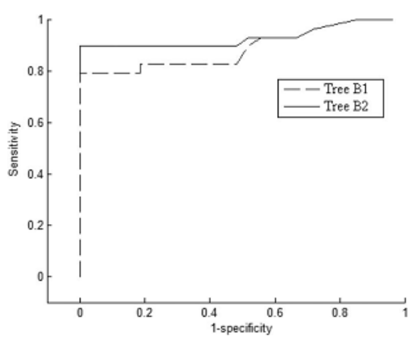
- Tree models

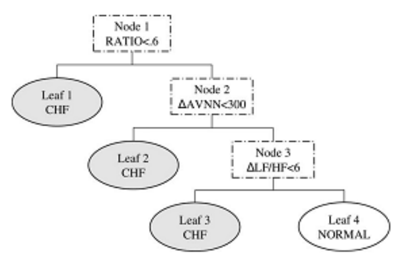


Excerpt classification decision tree

Methods

- Tree models





Subjects classification

Methods

D. Performance Measurements

BINARY CLASSIFICATION PERFORMANCE MEASURES

Measure (Abbreviation)	Formula
Accuracy (Acc)	$\frac{TP+TN}{TP+TN+FP+FN}$
Precision (Pre)	$\frac{TP}{TP+FP}$
Sensitivity (Sen)	$\frac{TP}{TP+FN}$
Specificity (Spe)	$\frac{TN}{FP+TN}$
Area Under the Curve (AUC)	$AUC = \frac{1}{2}\left(\frac{TP}{TP+FN}+\frac{TN}{TN+FP}\right);$

Results

CONFUSION MATRIX USING THE TREE B1

	Classified Normal	*Classified CHF*
Normal	54	0
CHF	6	23

CONFUSION MATRIX USING THE TREE B2

	Classified Normal	*Classified CHF*
Normal	54	0
CHF	3	26

TABLE IV
CONFUSION MATRIX PER NYHA USING THE TREE B1

	Classified Normal	*Classified CHF*
Normal	54	0
NYHA I	2	2
NYHA II	1	7
NYHA III	3	14

TABLE VI
CONFUSION MATRIX PER NYHA USING THE TREE B2

	Classified Normal	*Classified CHF*
Normal	54	0
NYHA I	1	3
NYHA II	1	7
NYHA III	1	16

	TP	FP	TN	FN	ACC	PRE	SEN	SPE	AUC
Tree B1	23	0	54	6	93	100	79	100	90
Tree B2	26	0	54	3	96	100	90	100	95
Asyali[35]	18	1	51	4	93	95	82	98	90
Isler [36]	29	3	51	0	96	91	100	94	97

Conclusion

- standard short-term HRV measures allow discriminating normal subjects from CHF patients
- sensitivity and specificity of 79.3% and 100%
- enhanced by 24 h ΔAVNN andΔLF/HF
- fully understandable set of rules easily expressed
- fully understandable, noninvasive, and low-cost ECG examinations for diagnosis of CHF.

Advanced Case (3)

- **Noninvasive Assessment of the Complexity and Stationarity of the Atrial Wavefront Patterns During Atrial Fibrillation**

- IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL. 57, NO. 9, SEPTEMBER 2010

Content

- Abstract
- Introduction
- Materials and Methods
- Results
- Conclusion

Abstract

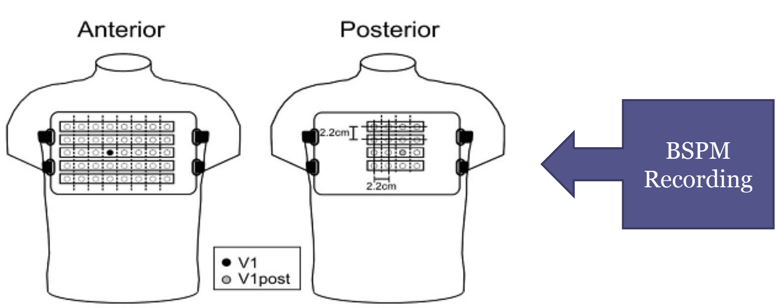
- Quantitatively evaluate AA in AF
- Use PCA to anylisis
- Evaluate the spatio-temporal organization
- discriminatory power analyzed

Introduction

- During atrial fibrillation (AF), the atrial tissue is activated by multiple wavelets showing uncoordinated patterns
- Distinguish between organized and disorganized states of AF
- Surface ECG has been demonstrated to be a valuable cost-effective tool for studying AF.
- By PCA, AA organization is evaluated quantitatively analyze the spatial complex and the temporal Stationarity.

Materials and Methods

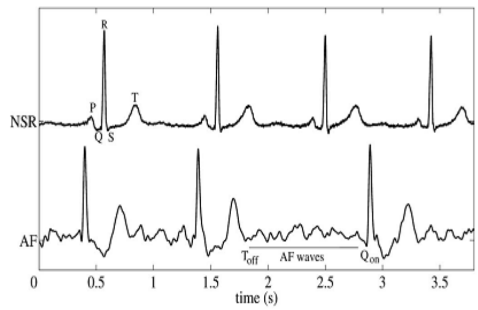
A. BSPM Data and Acquisition System



Materials and Methods

B. ECG Signal Preprocessing

- high-pass Chebyshev filte
- −3 dB cutoff frequency
- zero-phase notch filter 50Hz



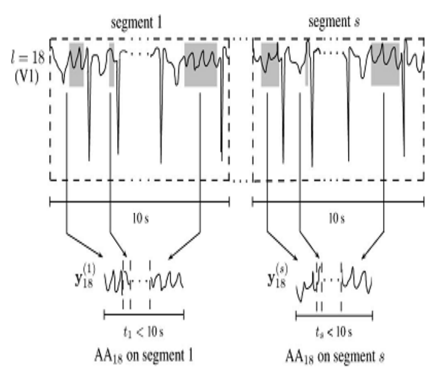
Materials and Methods

C. AA Recordings

Only TQ segments in the BSPM recording were Analyzed

Pan and Tompkins's QRS detection method

56-lead BSPM recording:



Materials and Methods

D. Principal Component Analysis

- ECG is a signalwith a high spatial redundancy
- PCA-minimizing the redundancy
- Produce mutually uncorrelated components

$$Y = MX \Rightarrow X = [M^T M]^{-1} M^T Y = M^{\sharp} Y$$

$$v_k = \frac{\sum_{i=1}^{k} \sigma_i^2}{\sum_{i=1}^{m} \sigma_i^2}.$$

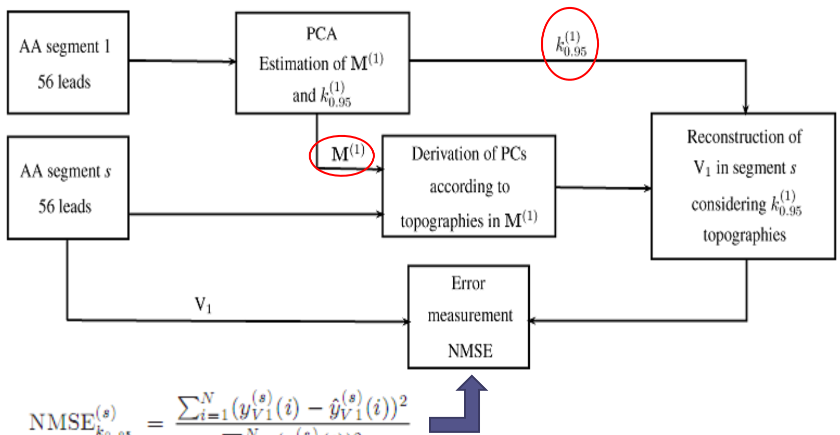
Materials and Methods

E. Assessment of Spatio-temporal Organization of the AA

- Evaluated as the spatial complexity and temporal stationarity of the wavefront pattern
  1) AA Spatial Complexity
     k (number of significant components)
  2) AA Temporal Stationarity
     NMSE

$$\hat{\mathbf{Y}}^{(s)} = \mathbf{M}_k^{(1)} \left[(\mathbf{M}_k^{(1)})^T \mathbf{M}_k^{(1)} \right]^{-1} (\mathbf{M}_k^{(1)})^T \mathbf{Y}^{(s)}$$
$$= \mathbf{M}_k^{(1)} (\mathbf{M}_k^{(1)})^{\sharp} \mathbf{Y}^{(s)}.$$

Materials and Methods



$$\mathrm{NMSE}_{k_{0.95}}^{(s)} = \frac{\sum_{i=1}^{N}(y_{V1}^{(s)}(i) - \hat{y}_{V1}^{(s)}(i))^2}{\sum_{i=1}^{N}(y_{V1}^{(s)}(i))^2}$$

Materials and Methods

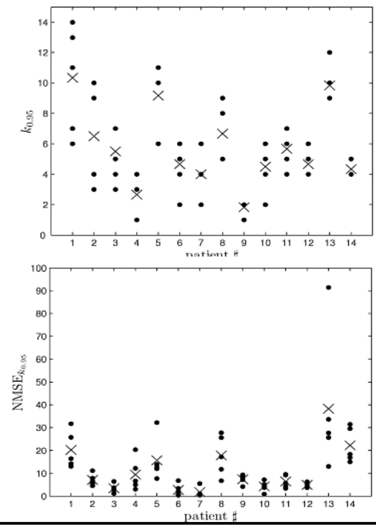
F. Cluster Analysis

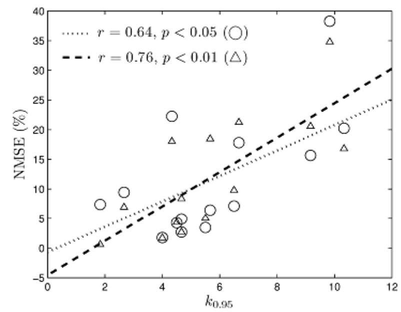
$$d = \sum_{j=1}^{K}\sum_{i=1}^{N}\|g_i^{(j)} - c_j\|^2 \qquad S(x) = \frac{b(x) - a(x)}{\max(a(x), b(x))}$$

G. Statistical Analysis

- *Mean values of parameter k*
- *Mean values of parameters NMSE*
- *Pearson's correlation coefficient r*
- *Statistical significances (Welch's t-test.)*

Results

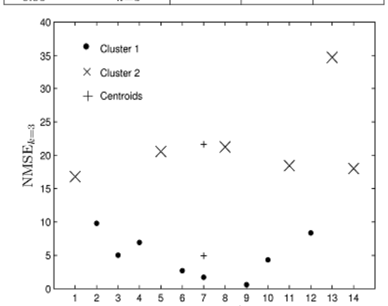




Results

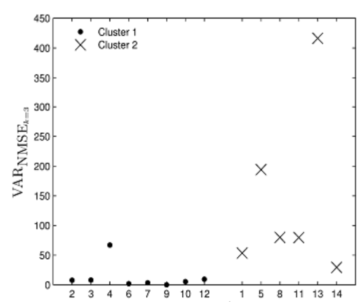
CLUSTERING QUALITY ASSESSMENT THROUGH AVERAGE SILHOUETTE WIDTH OF CLUSTERINGS $\bar{S}$

Clustering parameters	$\sharp K = 2$	$\sharp K = 3$	$\sharp K = 4$
$k_{0.95}$	0.679	0.637	**0.687**
$\mathrm{NMSE}_{k_{0.95}}$	0.677	**0.761**	0.645
$k_{0.95}$ & $\mathrm{NMSE}_{k_{0.95}}$	0.643	0.681	0.534
$\mathrm{NMSE}_{k=3}$	**0.700**	0.741	0.665
$k_{0.95}$ & $\mathrm{NMSE}_{k=3}$	0.642	0.691	0.550



MEAN PARAMETER VALUES FOR AA SPATIO-TEMPORAL ANALYSIS, FOR $\sharp K = 2$

Parameter	Cluster 1	Cluster 2	p-value
$k_{0.95}$	4.29±1.49	7.67±2.46	$p < 0.01$
$\mathrm{NMSE}_{k=3}$	4.94±3.25	21.64±6.64	$p < 10^{-4}$



Discussion

- The degree of organization in the AA during AF has been observed to be related to its chronification.

A. Comparison With Invasive Studies

B. Comparison With Noninvasive Studies

C. General Remarks and Limitations

Conclusion

- Spatio-temporal organization in the AA during AF can be evaluated from BSPM recordings.
- Reflection on the surface ECG of the spatial complexity and the temporal stationarity of its potential field spatial pattern
- Automated analysis of AF organization in surface recordings is possible
- Exploiting spatial diversity in AF analysis.

Advanced Case (4)

- **A Generic and Robust System for Automated Patient-Specific Classification of ECG Signals**

- IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL. 56, NO. 5, MAY 2009

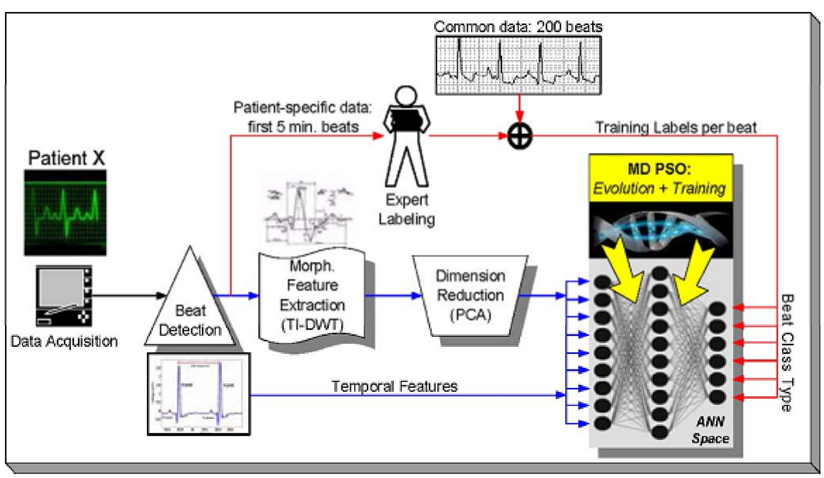
Content

- **Introduction**
- **ECG data processing**
- **MD PSO Technique for Automatic ANN Design**
- **Experimental Results**
- **Conclusion**

Introduction

- Each individual heartbeat of ECG waveform shows the time evolution of the heart's electrical activity.
- Disorder of rhythm or change will be detected by analysis of the ECG.
- Many algorithms for automatic detection and classification of ECG signals unreliable.
- Performance of ECG pattern classification depents on deatures extracted and classifier.
- Wavelet transform is an effcient tool

Introduction



Introduction

- Propose a multidimensional particle swarm optimization (MD PSO) technique to generic.
- Aim to achieve a high level of robustness with respect to the variations of the dataset
- Using standard ANNs such as traditional MLPs
- Make it applicable to any ECG dataset without any modifications

ECG data processing

A. ECG Data

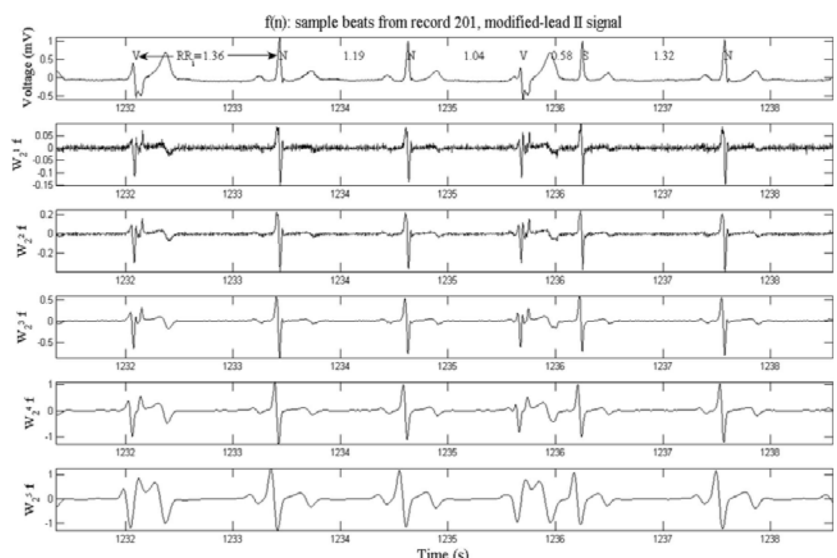
- MIT/BIH arrhythmia database
- AAMIECAR-1987
- Five heartbeat types:
  - N(beats originating in the sinus mode)
  - S (supraventricular ectopic beats (SVEBs))
  - V (ventricular ectopic beats (VEBs))
  - F(fusion beats)
  - Q (unclassifiable beats)

ECG data processing

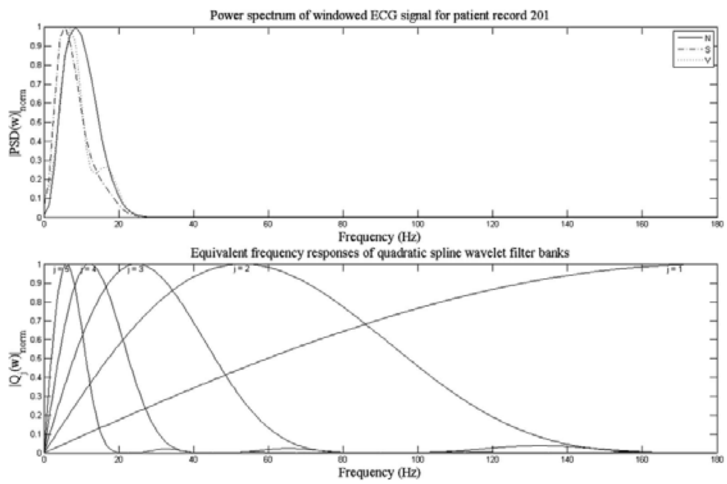
B. Feature Extraction Methodology

- Wavelet transform is used to extract morphological information from the ECG data
- Multirate filter bank (the pyramid decomposition)
- TI-DWT, only the scale parameter is sampled along the dyadic sequence
- A quadratic spline wavelet with compact support and one vanishing moment to make system efficient and robust.

ECG data processing



ECG data processing

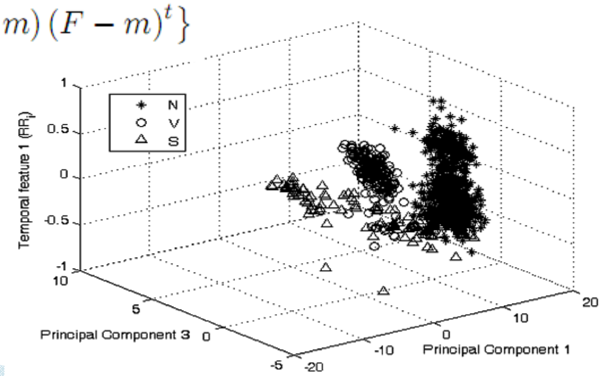


ECG data processing

C. Preprocessing by PCA

- To reduce dimensionality
- Karhunen-Lo´eve transform (KLT)

$$C_F = E\left\{(F - m)(F - m)^t\right\}$$



MD PSO Technique for Automatic ANN Design

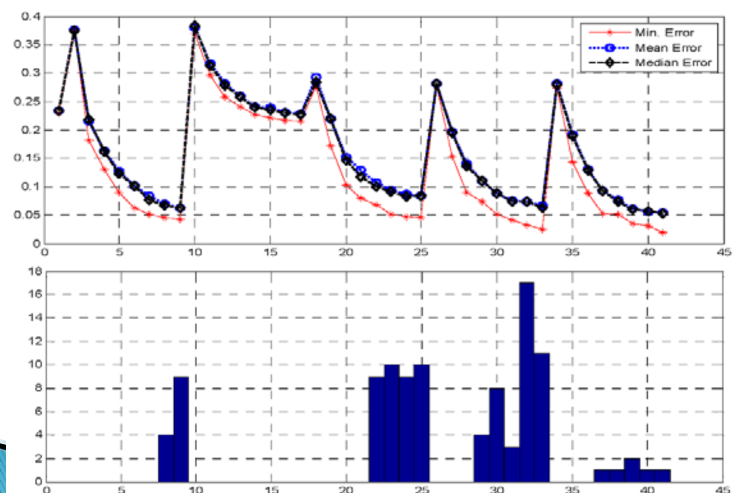
- A. MD PSO Algorithm
- B. MD PSO for Evolving ANNs

$$y_k^{p,l} = F(s_k^{p,l}), \text{ where } s_k^{p,l} = \sum_j w_{jk}^{l-1} y_j^{p,l-1} + \theta_k^l$$

$$\text{MSE} = \frac{1}{2PN_O} \sum_{p \in T} \sum_{k=1}^{N_O} \left(t_k^p - y_k^{p,O}\right)^2$$

Experimental Results

- A. MD PSO Optimality Evaluation



Experimental Results

- B. Classification Performance

SUMMARY TABLE OF BEAT-BY-BEAT CLASSIFICATION RESULTS FOR ALL 44 RECORDS IN MIT/BIH ARRHYTHMIA DATABASE

Ground Truth	Classification Result: N	S	V	F	Q
N	73019 (40532)	991 (776)	513 (382)	98 (56)	29 (20)
S	686 (672)	1568 (1441)	205 (197)	5 (5)	6 (5)
V	462 (392)	333 (299)	4993 (4022)	79 (75)	32 (32)
F	168 (164)	28 (26)	48 (46)	379 (378)	2 (2)
Q	8 (6)	1 (0)	3 (1)	1 (1)	1 (0)

Experimental Results

- C. Robustness

VEB AND SVEB CLASSIFICATION PERFORMANCE OF PROPOSED METHOD AND COMPARISON WITH THREE MAJOR ALGORITHMS FROM LITERATURE

Methods	VEB *Acc*	VEB *Sen*	VEB *Spe*	VEB *Ppr*	SVEB *Acc*	SVEB *Sen*	SVEB *Spe*	SVEB *Ppr*
Hu et al. [11] [1]	94.8	78.9	96.8	75.8	N/A	N/A	N/A	N/A
Chazal et al. [15] [1]	96.4	77.5	98.9	90.6	92.4	76.4	93.2	38.7
Jiang and Kong [16] [1]	98.8	94.3	99.4	95.8	97.5	74.9	98.8	78.8
Proposed [1]	97.9	90.3	98.8	92.2	96.1	81.8	98.5	63.4
Jiang and Kong [16] [2]	98.1	86.6	99.3	93.3	96.6	50.6	98.8	67.9
Proposed [2]	97.6	83.4	98.1	87.4	96.1	62.1	98.5	56.7
Proposed [3]	98.3	84.6	98.7	87.4	97.4	63.5	99.0	53.7

(%)	I	II	III	IV
VEB	98.3	98.2	98.3	98.0
SVEB	97.4	97.3	97.1	97.4

I: $R^1_{min} = \{11,8,4,5\}, R^1_{max} = \{11,16,8,5\}$, S=100, I=500

II: $R^1_{min} = \{11,8,4,5\}, R^1_{max} = \{11,16,8,5\}$, S=250, I=200

III: $R^1_{min} = \{11,8,4,5\}, R^1_{max} = \{11,16,8,5\}$, S=80, I=200

IV: $R^1_{min} = \{11,6,6,3,5\}, R^1_{max} = \{11,12,10,5,5\}$, S=400, I=500

Conclusion

- Proposed an automated patient-specific ECG heartbeat classifier.
- The TI-DWT and the PCA are the principal signal processing tools
- Standard MLP classifiers are automatically designed using the proposed MD-PSO technique without performance loss.

Advanced Case (5)

- **Multilead ECG Delineation Using Spatially Projected Leads From Wavelet Transform Loops**
- IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL. 56, NO. 8, AUGUST 2009

Content

- Introduction
- Materials and Methods
- Results
- Discussion
- Conclusion

Introduction

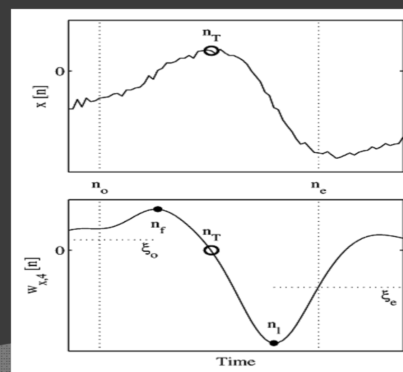
- The different phases of the heart's electrical activity are mapped to the waves in the ECG
- Detection and delineation system for different waveforms.
- The WT is a suitable tool for ECG automatic delineation.
- Global feature for all the leads
- A multilead (ML) methodology regarding boundaries location is proposed and validated

Materials and Methods

A. SL Delineation

- WT is implemented using the algorithm atrous to obtain waveforms

- Zero -> peak
- Max-> slope
- Threshold-> boundary



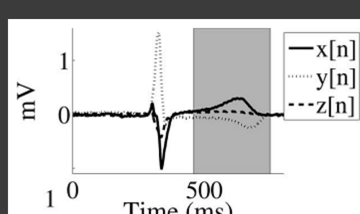
Materials and Methods

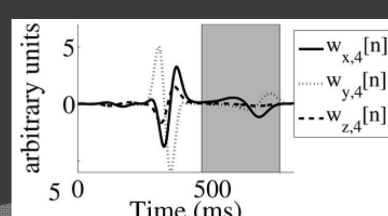
B.SL Selection Rule for ML Signals

C.ML Delineation

- Three simultaneous orthogonal leads

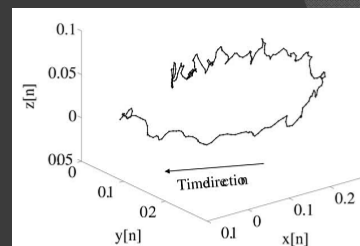
$$s[n] = [x[n], y[n], z[n]]^T$$



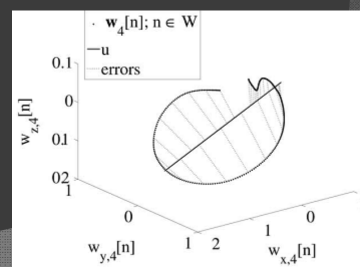


Materials and Methods

- VCG loop of the T wave



- w4 [n] loop of the T wave



Materials and Methods

- General Algorithm for ML Boundary Location
  - Use TLS update the WT loop to fit the VCG
- Specific Parameters for QRS Complex Boundaries

$$W^{(i)} = \mathrm{Q}^{(i)} = \left[n_{\mathrm{QRS},o}^{(i-1)} - 4s_{\mathrm{CSE}(\mathrm{QRS}_{\mathrm{on}})},\ n_{\mathrm{QRS},f}^{(i-1)}\right]$$

$$W^{(i)} = \mathrm{S}^{(i)} = \left[n_{\mathrm{QRS},l}^{(i-1)},\ n_{\mathrm{QRS},e}^{(i-1)} + 4s_{\mathrm{CSE}(\mathrm{QRS}_{\mathrm{end}})}\right]$$

- Specific Parameters for T-Wave Boundaries

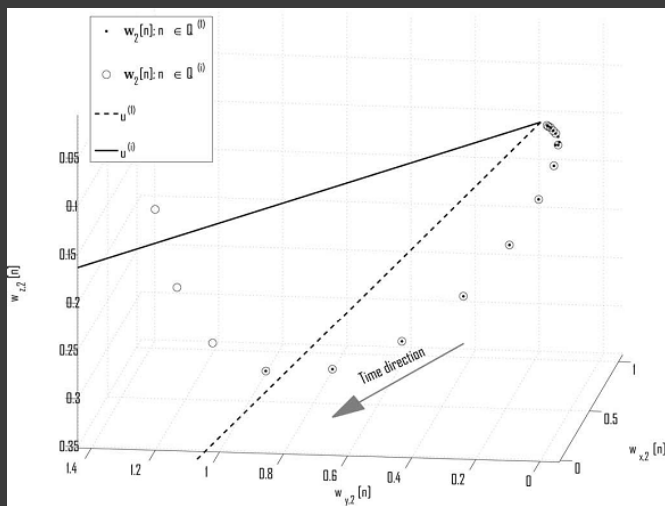
search window for *T onset* at iteration (i) is updated as

$$W^{(i)} = \mathrm{T}_o^{(i)} = \left[n_{\mathrm{T},o}^{(i-1)} - 4s_{\mathrm{CSE}}(\mathrm{T}_{\mathrm{on}});\ n_{\mathrm{T},f}^{(i-1)}\right]$$

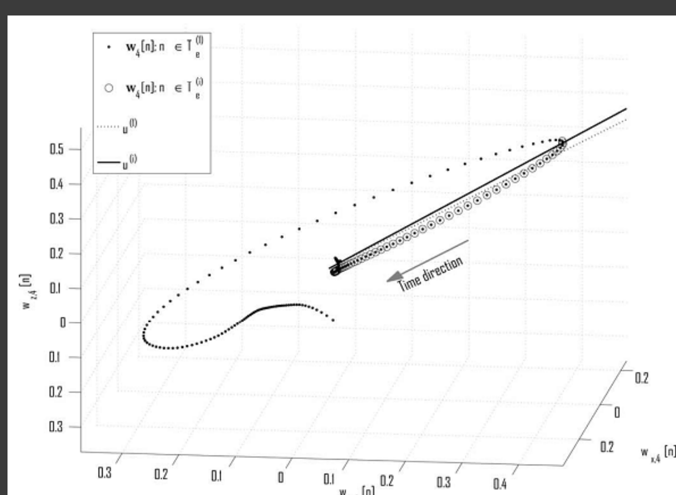
and the search window for *T end* is actualized as

$$W^{(i)} = \mathrm{T}_e^{(i)} = \left[n_{\mathrm{T},l}^{(i-1)};\ n_{\mathrm{T},e}^{(i-1)} + 4s_{\mathrm{CSE}}(\mathrm{T}_{\mathrm{end}})\right]$$

Materials and Methods

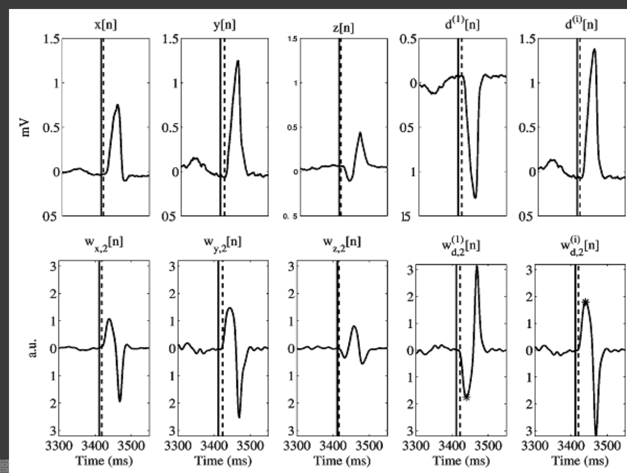


Materials and Methods



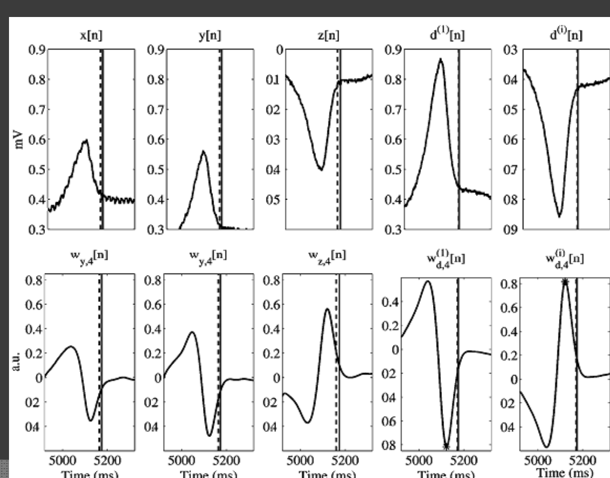
Materials and Methods

- QRS onset:



Materials and Methods

- T wave end:



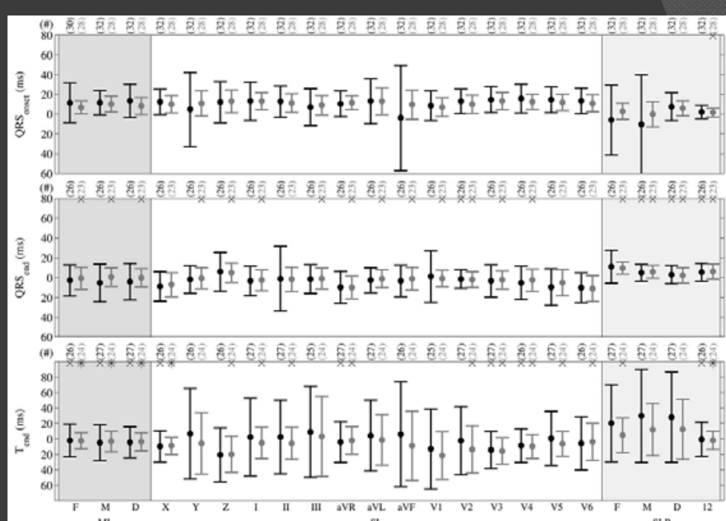
Materials and Methods

D. Validation

- Common Standards for Electrocardiography ML measurement database(CSEDB)
- QTDB
- Physikalisch-Technische Bundesanstalt (PTB)
- sensitivity S = 100 TP/(TP + FN)
- 1) Loose criterion: s< 2sCSE
- 2) Strict criterion: s<sCSE

Results

Delineation results in CSEDB



Results

OTHER PUBLISHED DELINEATION SYSTEMS WITH SELECTION RULES VALIDATED OVER CSEDB

	[5]	[16]	[13]
QRS onset			
(#/32)	(30)	(32)	(NR)
$m_\varepsilon \pm s_\varepsilon$	-2.1 ± 7.4	0.9 ± 3.6 ×	$NR \pm 2.0$ *
QRS end			
(#/27)	(25)	27	(NR)
$m_\varepsilon \pm s_\varepsilon$	-0.2 ± 3.6×	-0.6 ± 7.1	$NR \pm 4.0$ ×
T end			
(#/27)	(26)	NA	(NR)
$m_\varepsilon \pm s_\varepsilon$	2.6 ± 10.5*	NA	NR±20.0 ×

QRS BOUNDARIES DELINEATION RESULTS IN QTDB. (a) QRS COMPLEX ONSET. (b) QRS COMPLEX END

(a)

		ML	lead 1 SL	lead 2 SL	best mark
QTDB 1 (7 files)	# beats / 312	293	312	312	312
	$Se(\%)$	94	100	100	100
	$m_\varepsilon \pm \bar{s}_\varepsilon$, ms	6.4 ± 10.6	4.7 ± 10.8	12.3 ± 11.5	5.3 ± 8.7
QTDB 2 (57 files)	# beats / 1908	1885	1907	1906	1907
	$Se(\%)$	99	100	100	100
	$m_\varepsilon \pm \bar{s}_\varepsilon$, ms	5.9 ± 11.3	5.5 ± 10.5	6.6 ± 11.2	4.5 ± 7.8
QTDB 3 (34 files)	# beats / 1192	1132	1179	1188	1192
	$Se(\%)$	95	99	100	100
	$m_\varepsilon \pm \bar{s}_\varepsilon$, ms	10.4 ± 11.3	11 ± 14.7	9.3 ± 10.8	8.6 ± 8.6
all (98 files)	# beats / 3412	3310	3398	3406	3411
	$Se(\%)$	97	100	100	100
	$m_\varepsilon \pm \bar{s}_\varepsilon$, ms	7.5 ± 11.2	7.3 ± 12	7.9 ± 11.1	6 ± 8.2

Discussion

- Globally, ML allowed an error dispersion similar to that obtained using SLR over the 12 leads
- The automatic procedures are marking the QRS onset on CSEDB files later than the referees
- The ML over the VCG was able to provide, from only three ECG leads
- Among the VCG systems considered, lead set F achieved the best global performance.
- With respect to ML delineation using only two leads global results are similar to the worse SL result for QRS
- A better quantification of the true improvement achieved by the proposed ML method

Conclusion

- A novel ML WT-based strategy for ECG boundaries delineation was proposed
- Evaluated with respect to the QRS and T-wave boundaries.
- ML approach automatic delineation by constructing a WT signal more fit for specific boundary location.
- More robust and more accurate boundaries locations