ALGORITHMS TO DETECT TRANSIENT ST SEGMENT EPISODES

- Basic stages of ECG signal processing
- True ischaemic ST segment morphology changes
- Myocardial ischaemia
- Detecting transient ischaemic ST segment episodes
- Problems of automated ischaemia analysis
- Derivation of time-domain diagnostic feature vectors
- Derivation of orthonormal function model transform-based morphologic feature vectors
- Time series of diagnostic and morphologic feature vectors
- Estimating performance of ST episode detection

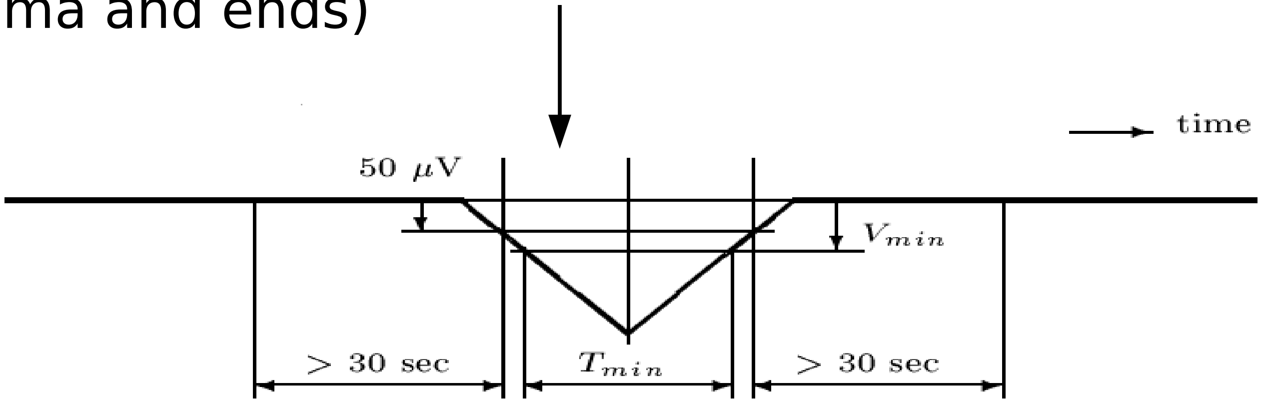
Basic stages of ECG signal processing

- *ECG filtering*
- *QRS complex detection*

  → (Wave delineation)
- *QRS complex classification*

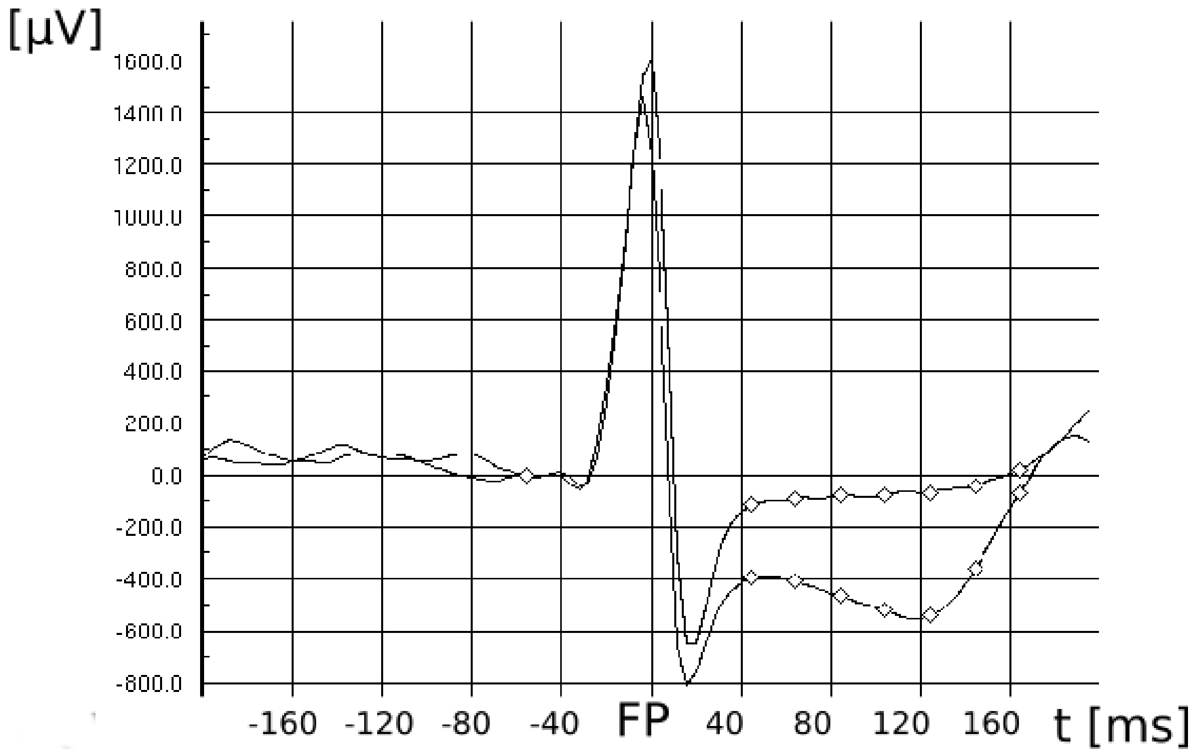
  → (Rhythm classification)

  → *Ischaemia detection* (*classifying ischaemic events*, detecting transient ischaemic episodes, and their precise beginnings, extrema and ends)

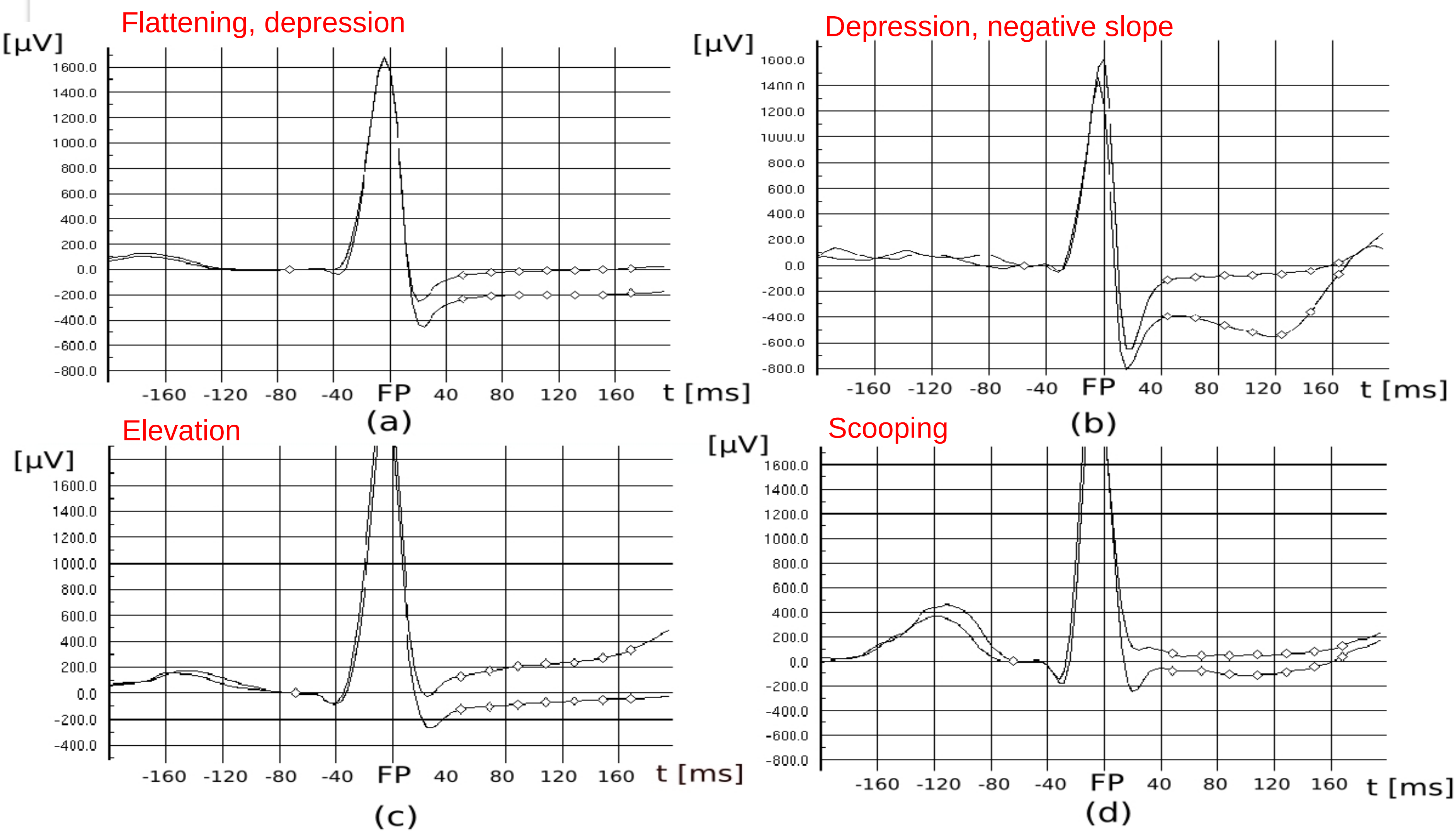


True ischaemic ST segment morphology changes

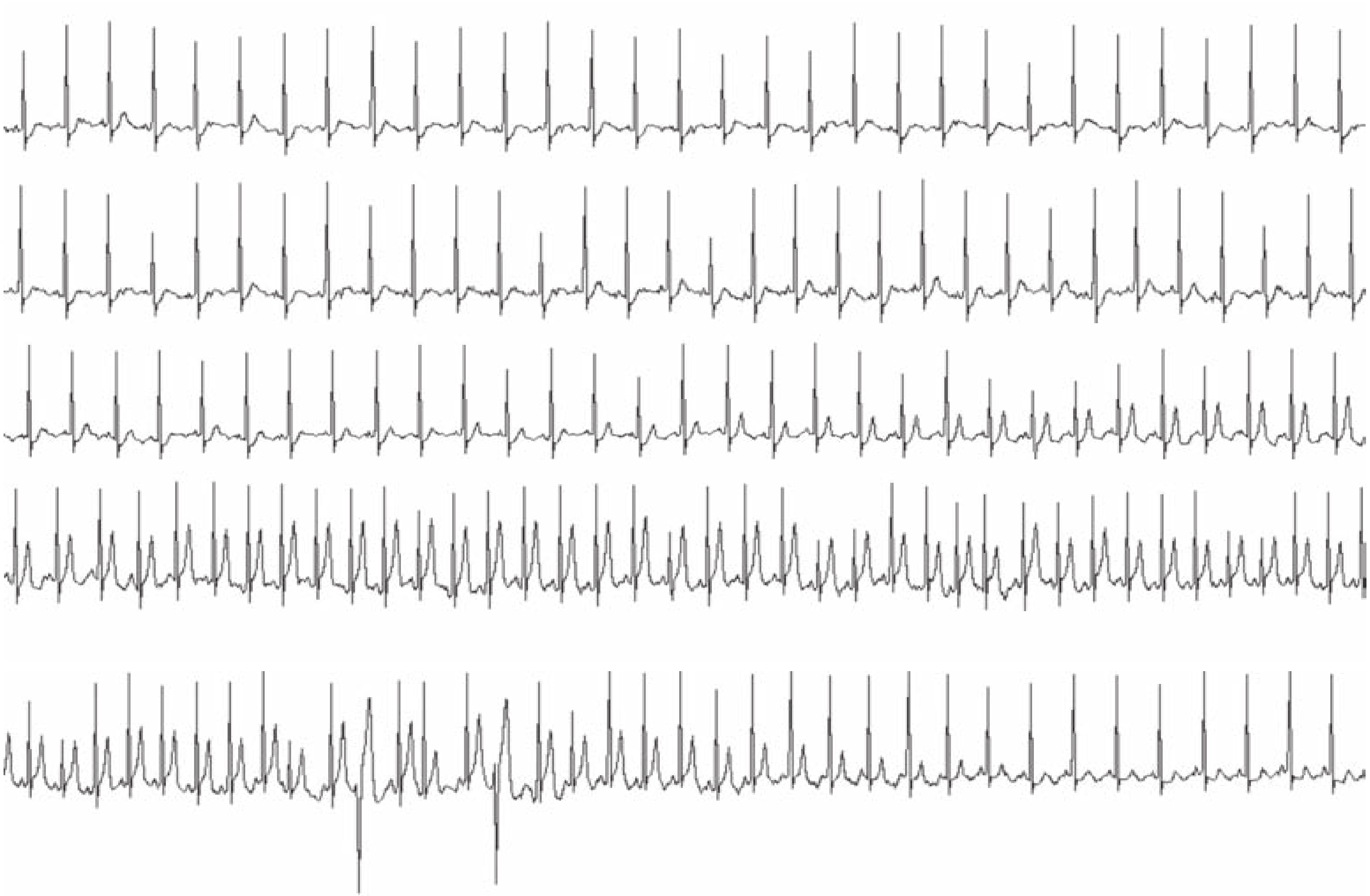
- Normal and ischaemic heart beat



True ischaemic ST segment morphology changes

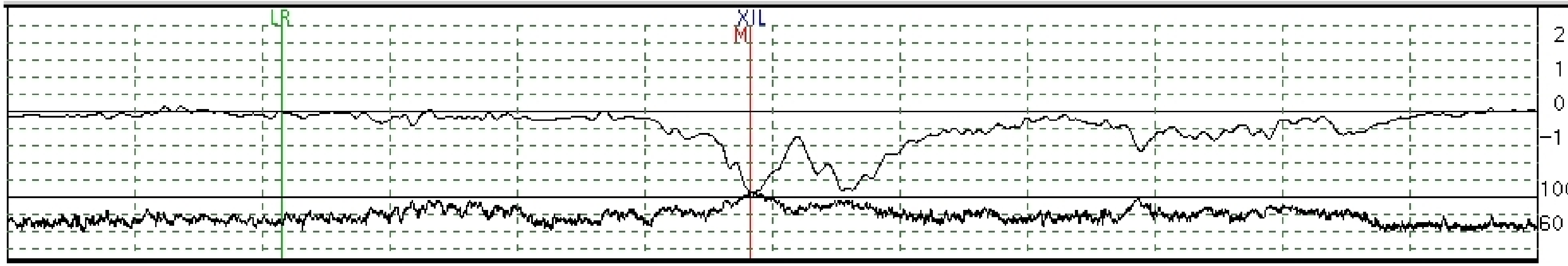


Myocardial ischaemia

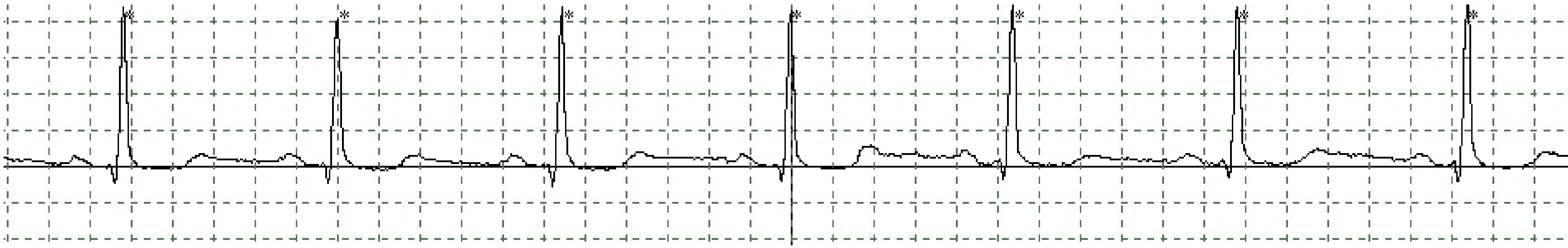


Myocardial ischaemia

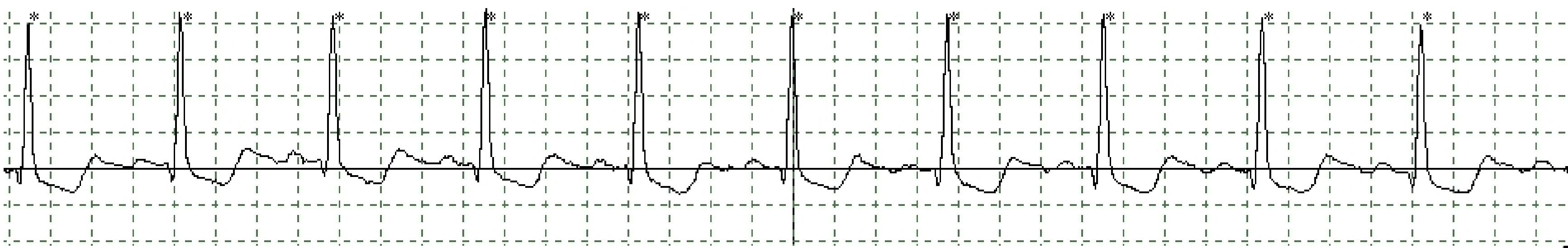
ST segment level and heart frequency



Local reference (LR)

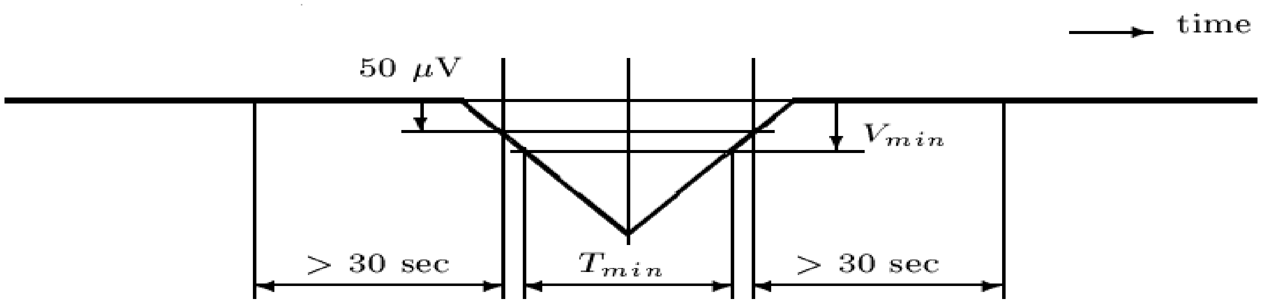


Marker (M) QRS ? ST ?



Detecting transient ischaemic ST segment episodes

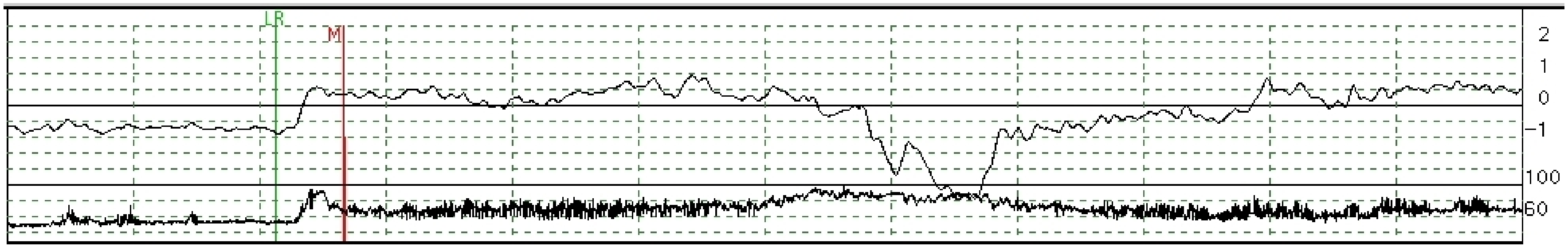
- Detect transient ischaemic ST segment episodes within time series of feature vectors



Problems of automated ischaemia analysis

- Shift of the mean electrical axis of the heart – body position change

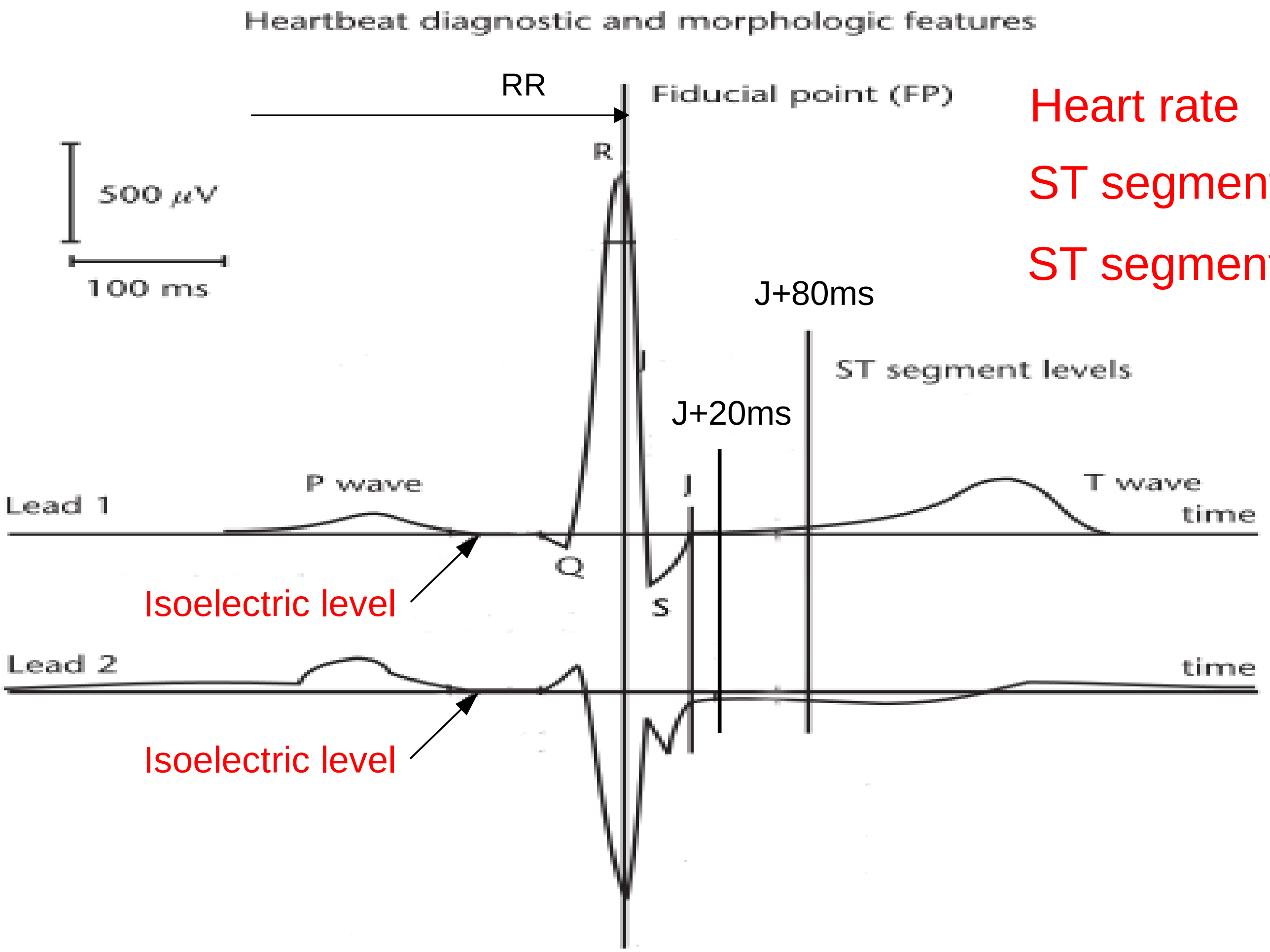
ST segment level and heart frequency



Reference (LR)

Marker (M) QRS ? ST ?

Derivation of time-domain diagnostic feature vectors



Heart rate

ST segment level

ST segment slope

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Derivation of time-domain diagnostic feature vectors

- Heart rate, *HR(j)*, ST segment level, $s_l(i,j)$, and ST segment slope, $s_s(i,j)$

  i - the lead number, *j* - the heartbeat number

  FP(j) - Fiducial Point

  a(i,j) - amplitude of ST segment level at the point *J*+80*ms*

  $a_{20}(i,j)$ - amplitude of ST segment level at the point *J*+20*ms*

  z(i,j) - isoelectric level

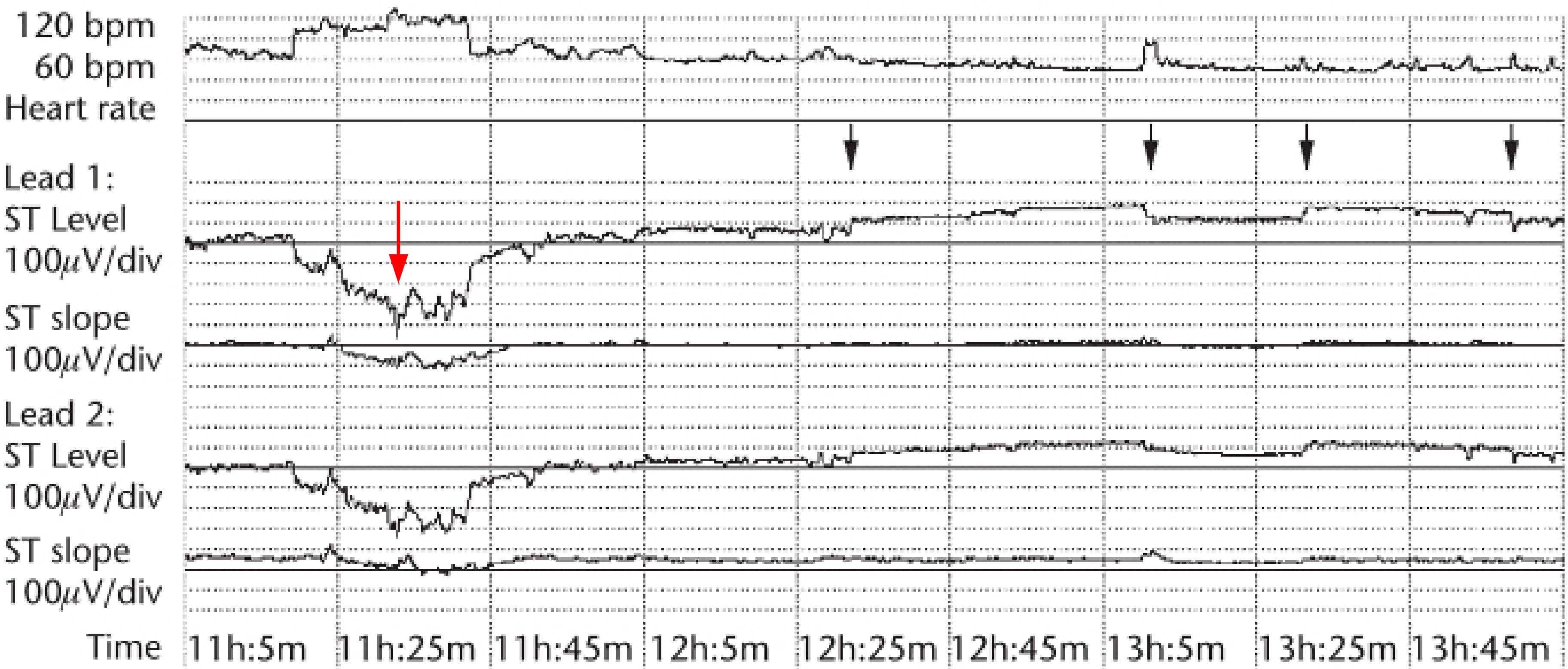
$$HR(j) = \frac{1}{FP(j) - FP(j-1)} \cdot 60 \; [\text{beats min}^{-1}]$$

$$s_l(i,j) = a(i,j) - z(i,j)$$

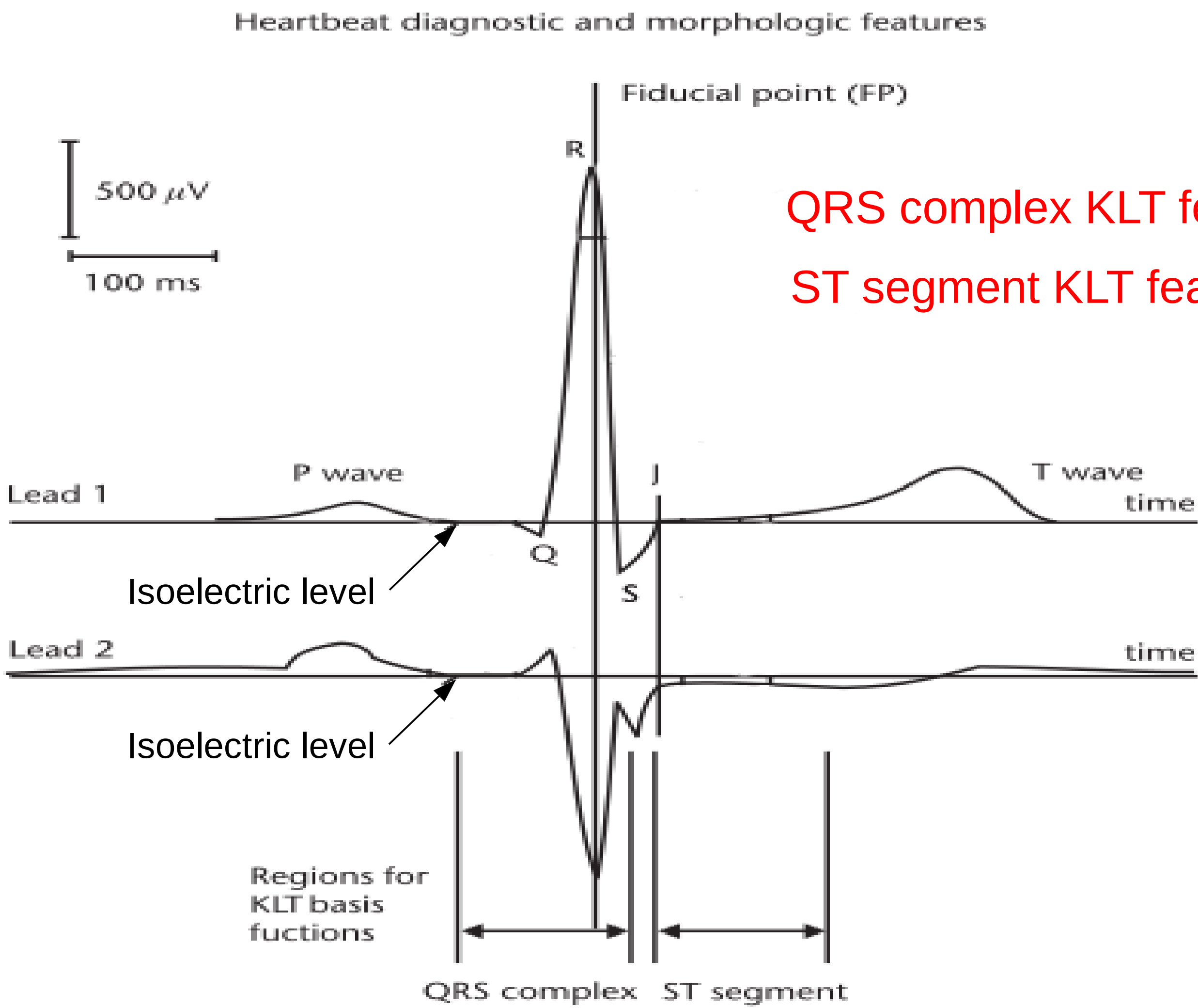
$$s_s(i,j) = a(i,j) - a_{20}(i,j)$$

Derivation of time-domain diagnostic feature vectors

- Heart rate, ST segment level, and ST segment slope



Derivation of orthonormal function model transform–based morphologic feature vectors



QRS complex KLT feature vector

ST segment KLT feature vector

Derivation of orthonormal function model transform– based morphologic feature vectors

- The Karhunen-Loéve Transform (KLT)
  - The KLT is orthonormal transform (given morphology (pattern vector) is represented with uncorrelated KL basis functions)
  - Applying the KL basis functions on a pattern vector yields the KL feature vector (KL coefficients)
  - The KLT allows accurate representation of pattern vectors and their subtle features
  - The KLT allows optimal distinguishing between clean and noisy pattern vectors in the sense that the expected least mean squared error (MSE) obtained by approximating a given pattern of a random process using any given number of the first few coefficients is minimal in comparison to other suboptimal transforms

Derivation of orthonormal function model transform–based morphologic feature vectors

- The QRS complex KL basis functions spread:
  - from FP – 96 ms to FP + 24 ms
- The ST segment KL basis functions spread:
  - from FP + 40 ms to FP + 160 ms

Derivation of orthonormal function model transform–based morphologic feature vectors

- Covariance matrix
- Basis functions are eigenvectors of covariance matrix, ***R*,**

$$\boldsymbol{R} = E\left\{ \left(\boldsymbol{x} - \boldsymbol{\mu}_{\boldsymbol{0}}\right) \left(\boldsymbol{x} - \boldsymbol{\mu}_{\boldsymbol{0}}\right)^T \right\}$$

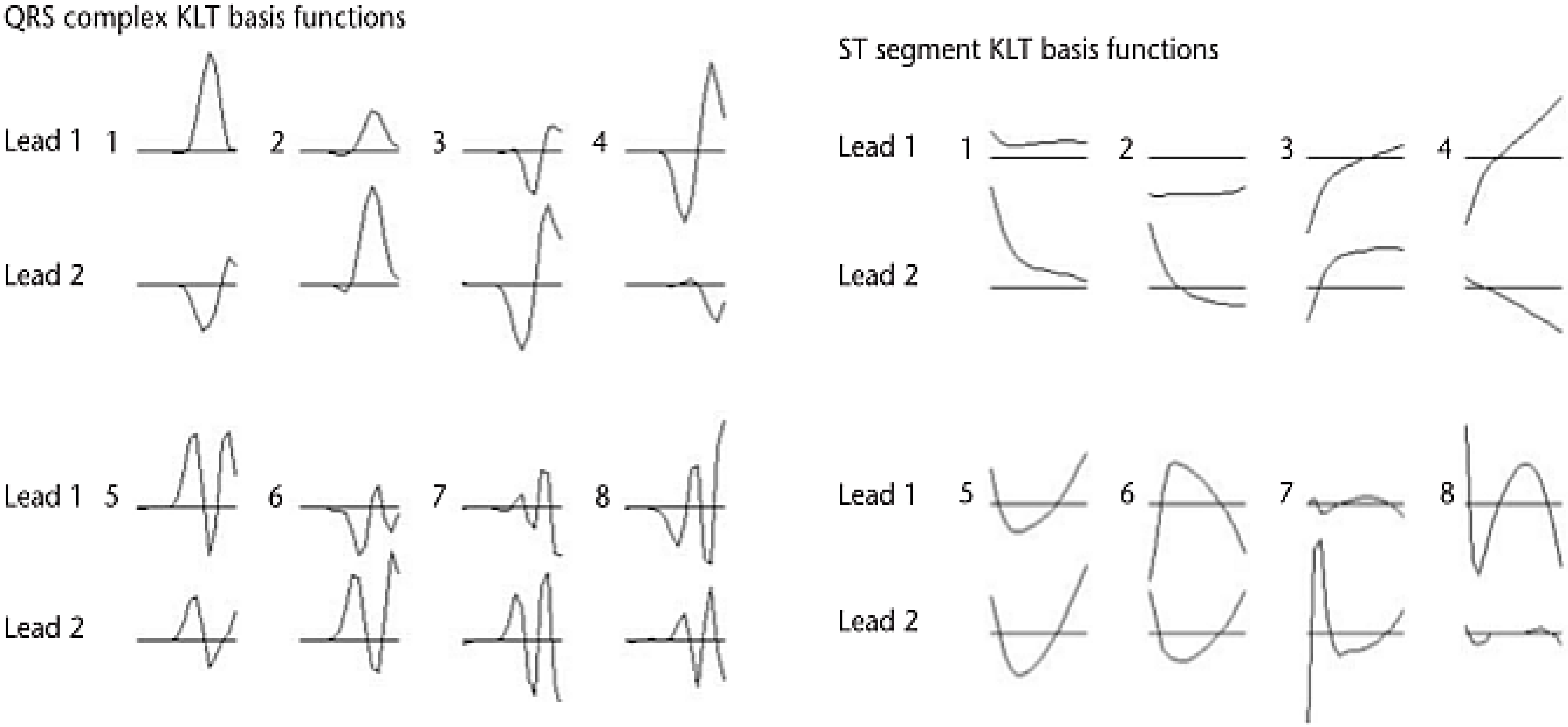
where ***x*** is a pattern vector and the mean vector $\boldsymbol{\mu}_0$ is defined as:

$$\boldsymbol{\mu}_{\boldsymbol{0}} = E\left\{\boldsymbol{x}\right\} \qquad \forall\, \boldsymbol{x}$$

and eigenvalues, σ_i, of the covariance matrix, ***R***, are standard deviations of the coefficients

- Number of pattern vectors (744.840) taken from the European Society of Cardiology ST-T Database (ESC DB)

Derivation of orthonormal function model transform–based morphologic feature vectors



Derivation of orthonormal function model transform–based morphologic feature vectors

- If the KLT is applied to the pattern vector ***x***, then a new feature vector ***y*** is obtained:

$$\boldsymbol{y} = \boldsymbol{\Phi}^{T} \boldsymbol{x}$$

where $\boldsymbol{\Phi}$ is the matrix of KLT basis functions (i.e., the matrix of eigenvectors of the covariance matrix ***R***). Components of such a feature vector ***y*** (of such a KLT feature vector) are termed as KLT coefficients.

Derivation of orthonormal function model transform–based morphologic feature vectors

- Euclidean and Mahalanobis distance measures

$$E^2(Y,Z) = \sum_i (y_i - z_i)^2 \qquad d^2(Y,Z) = \sum_i \left(\frac{y_i}{\sigma_i} - \frac{z_i}{\sigma_i} \right)^2$$

$$\sigma_1 \geq \sigma_2 \geq \ldots \geq \sigma_N \geq \ldots \geq \sigma_M$$

where σ_i are eigenvalues of the covariance matrix, ***R***, i.e., standard deviations of the coefficients

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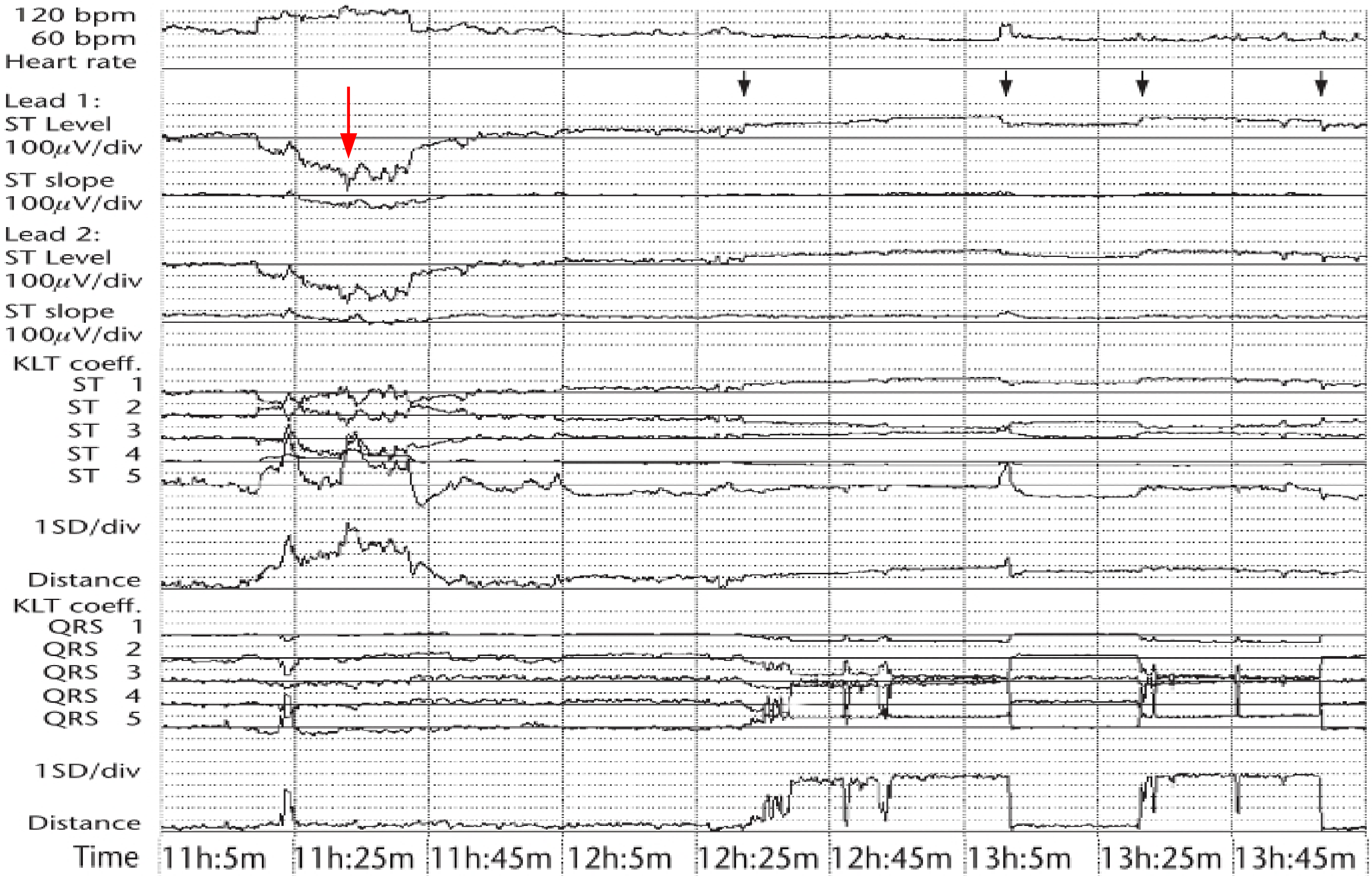
Time series of diagnostic and morphologic feature vectors



Estimating performance of ST episode detection

(LTST DB, Protocol B, 908 combined ST segment episodes)
(Time domain and KLT approach)

Se		Algorithm	
		ST epis	Other
Ref	ST epis	723	185
Ref	Other	-	-

+P		Algorithm	
		ST epis	Other
Ref	ST epis	750	-
Ref	Other	208	-

ST epis – Combined ST segment episodes

Se = 79.6%   +P = 78.3%