

Biometric Authentication Using Informative Components of a Spectrogram Matrix

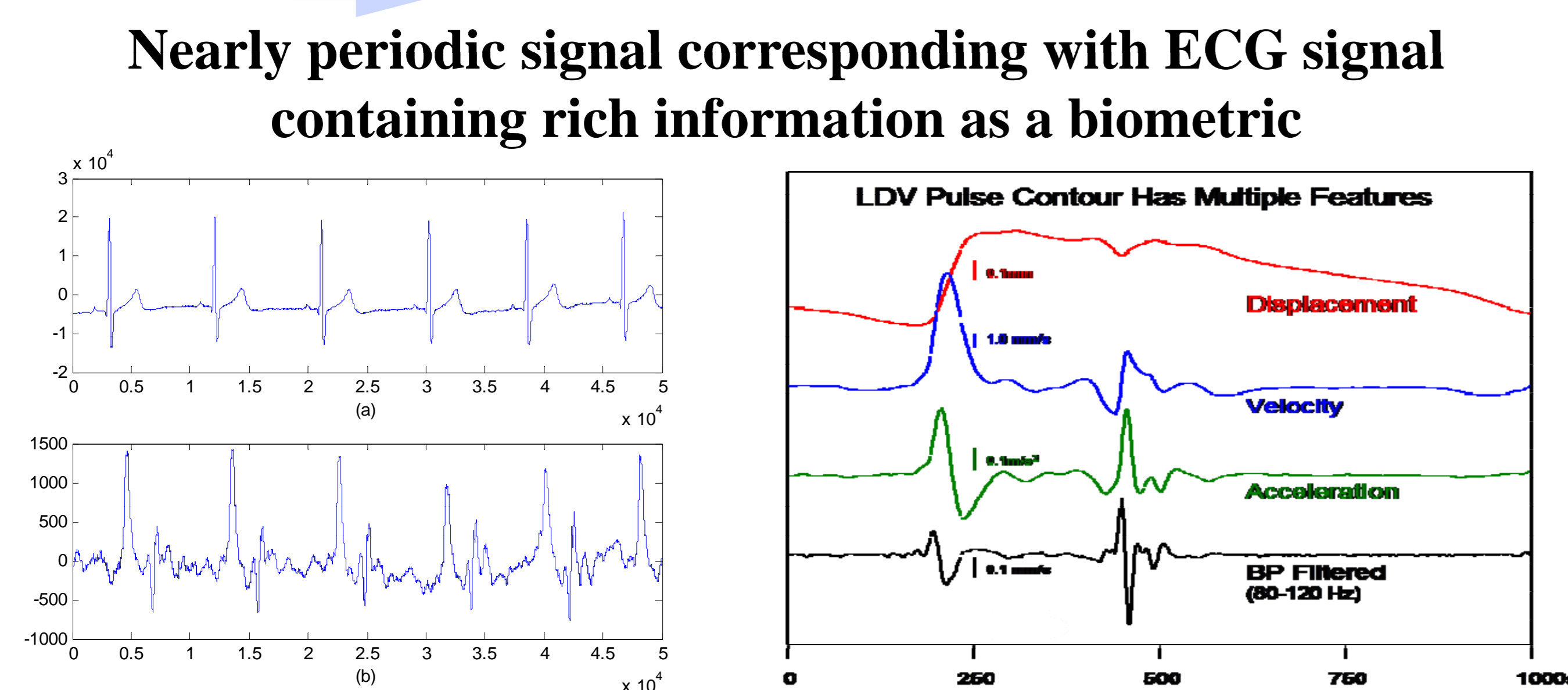
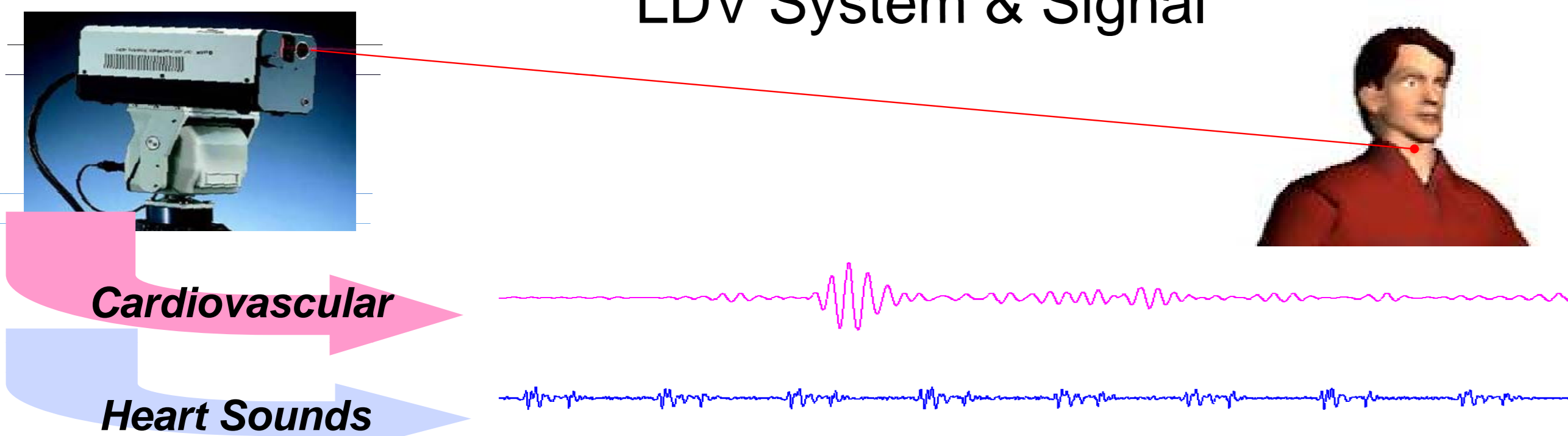
Abstract

A novel approach using mechanical physiological activity as a biometric marker is proposed. Pulse signals is acquired from Laser Doppler Vibrometry (LDV) system, which is used to sense activity in the region of the carotid artery, related to arterial wall movements associated with the central blood pressure pulse [5]. A statistical model is created for the spectrogram matrix of the acquired signal and is applied to evaluate the biometric feasibility of the pulse signal.

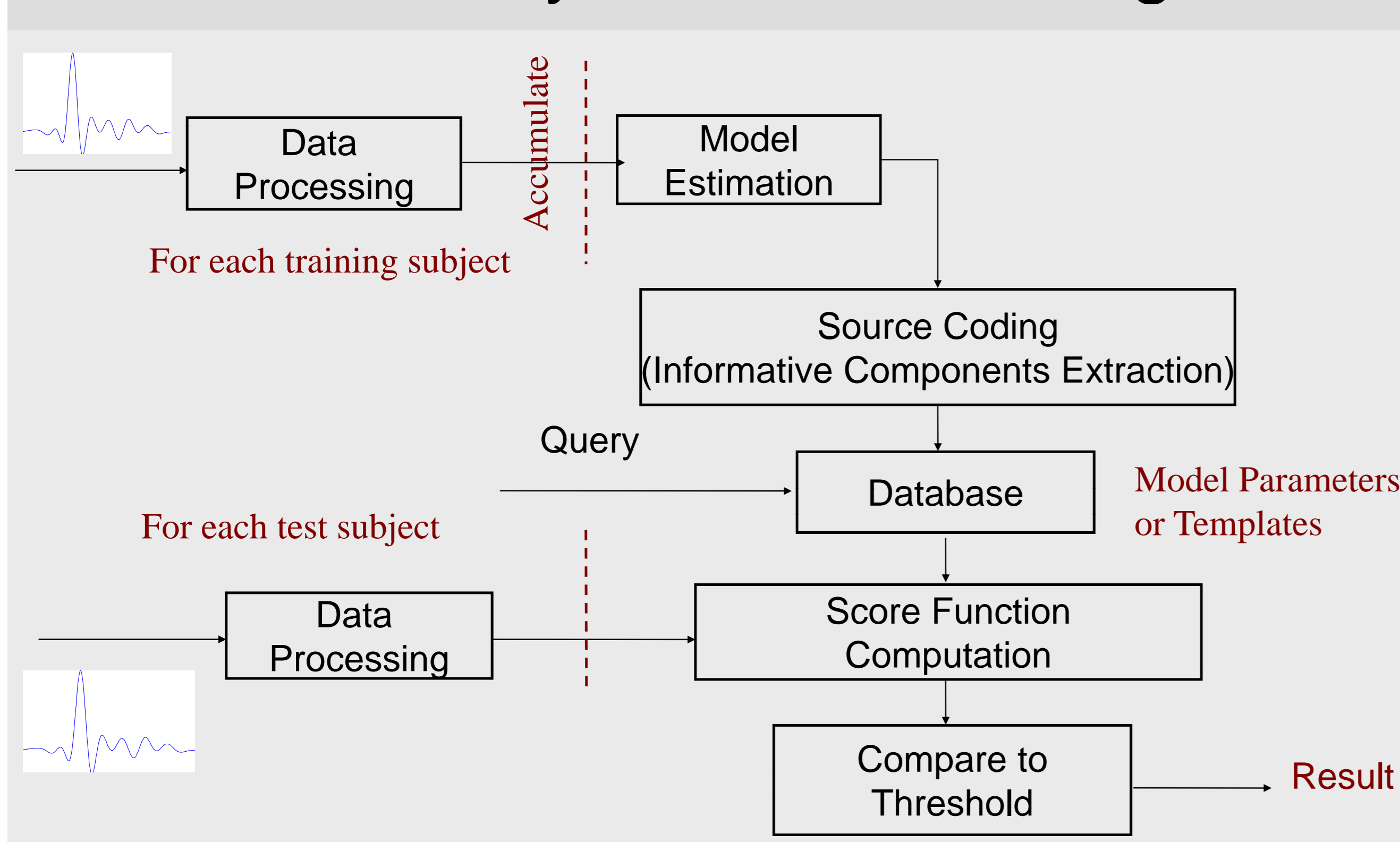
The idea of thresholding method for dimensionality reduction is to avoid the 'peaking phenomenon', caused by the small size of training data [1]. We apply this idea to extract informative components from the high dimensional spectrogram matrix. The relative entropy measures the distance between an individual model and a nominal model for each time-frequency bin separately. The sum of each bin's relative entropy gives the information rate of each individual model, which may determine how unique this model is. This method works well for non-distorted probability distributions in training and testing. The log-likelihood ratio is calculated as the score function for biometric authentication.

Currently, this approach achieves an inter-session equal error rate of 9% [5].

LDV System & Signal



Biometric System for LDV Signal

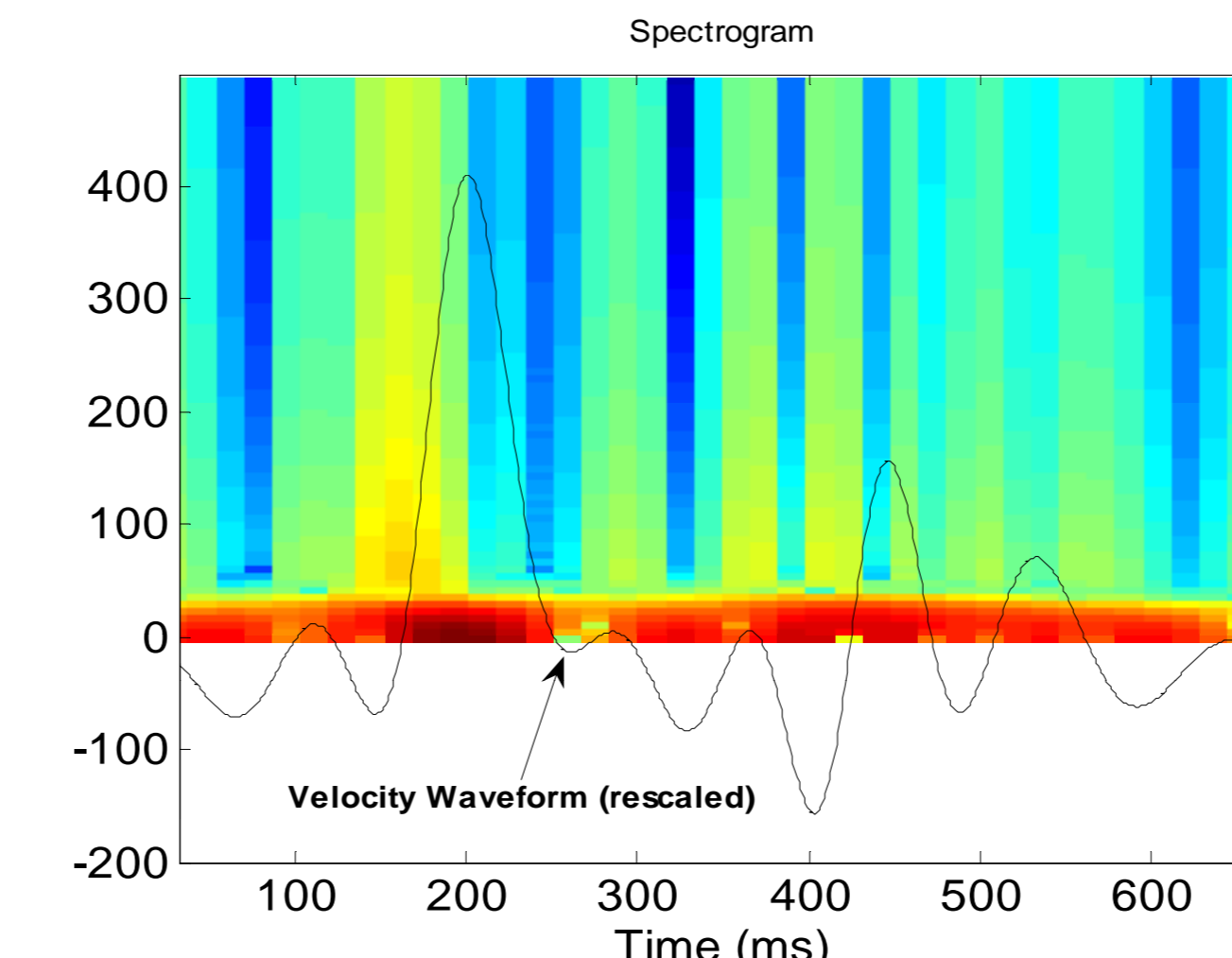


Time-Frequency Decomposition

- Spectrogram as a time-frequency distributed energy picture of a LDV pulse signal could be a potential pattern [2]
- Signal is decomposed by short-time Fourier transform
- Spectrogram is the magnitude of

$$X_n(e^{j\omega_k}) = \sum_{m=-\infty}^{\infty} w(n-m)x(m)e^{j\omega_k m}$$

- High energy concentrates on low frequency range



Dimension Reduction and Informative Component Extraction

- Peaking phenomenon causes the loss of classifiability
- Training reference template under small sample size with high dimensionality increases error
- Thresholding function $d(\cdot, \cdot)$ measures discriminating information
- Discarding dimensions with less discriminating information improves performance
- Modified binary test and the modified log-likelihood ratio are created [1]

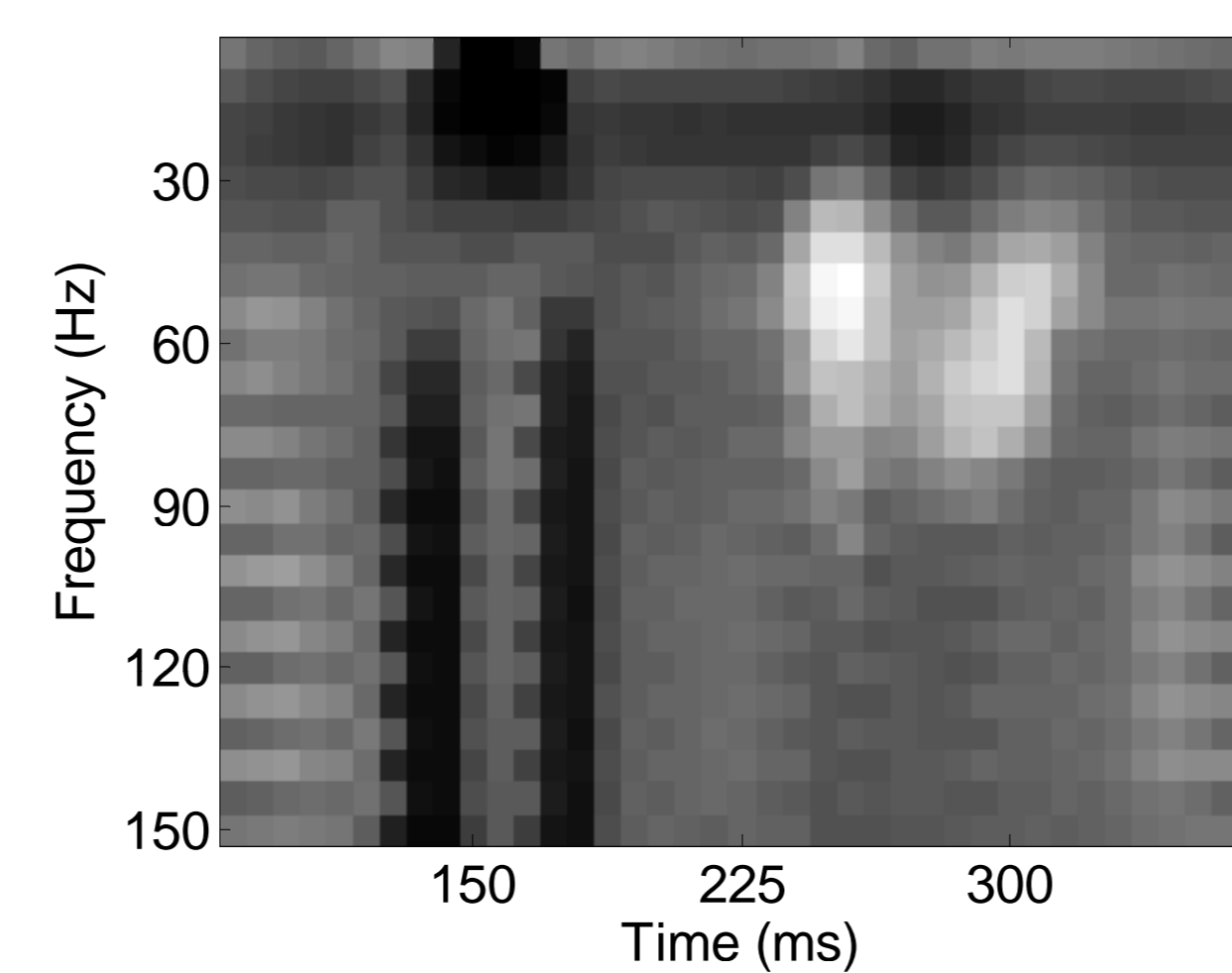
$$H_1, \text{ if } \tilde{\Lambda} \geq 0$$

$$H_2, \text{ otherwise}$$

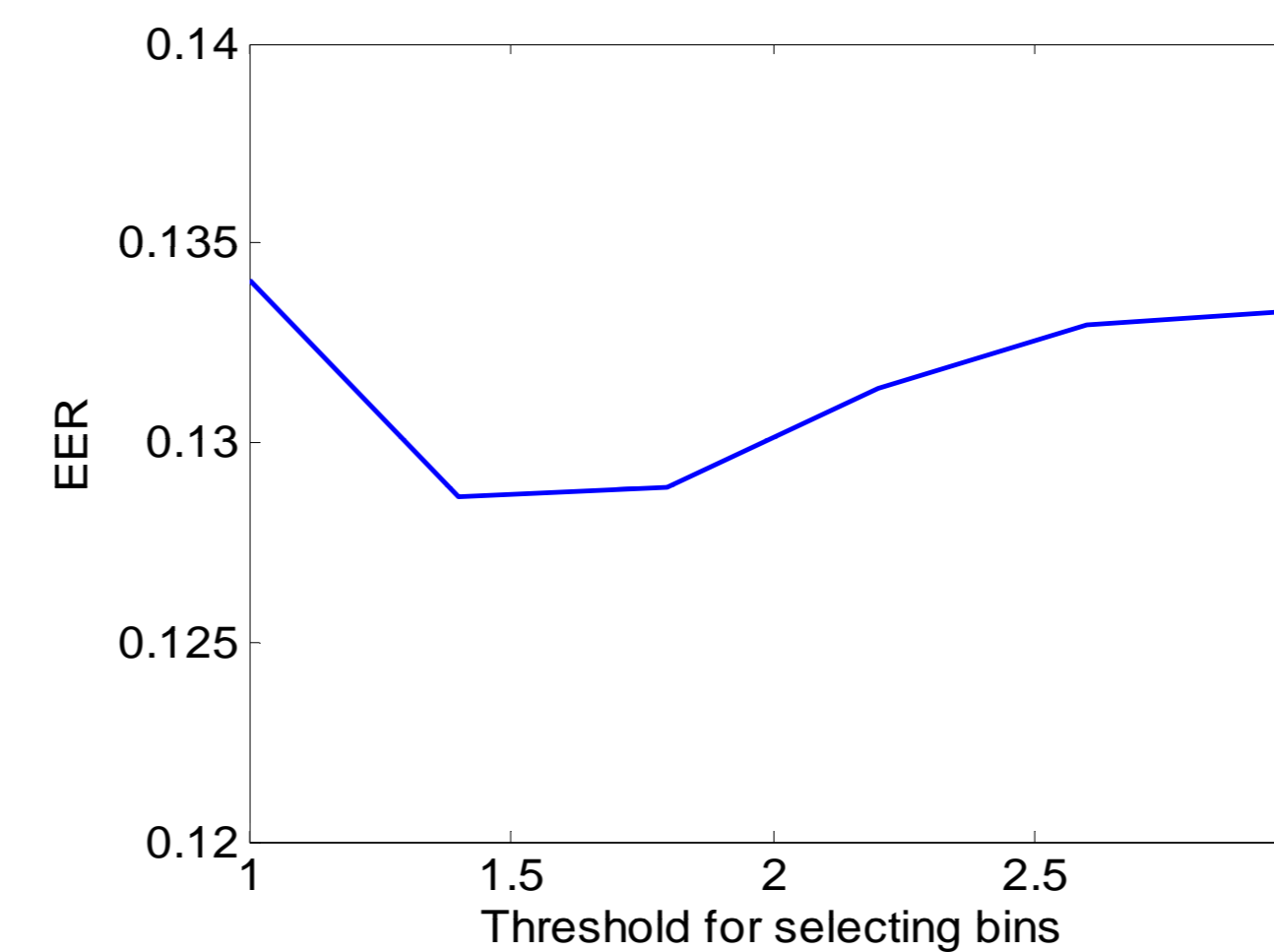
$$\tilde{\Lambda} = \sum_{l=1}^n \left\{ \log \left[\frac{p_1(R(l) | \hat{\theta}_1(l))}{p_0(R(l) | \varphi(l))} \right] I_{d_i(\hat{\theta}_1(l), \varphi(l)) > \kappa} - \log \left[\frac{p_2(R(l) | \hat{\theta}_2(l))}{p_0(R(l) | \varphi(l))} \right] I_{d_i(\hat{\theta}_2(l), \varphi(l)) > \kappa} \right\}$$

Redundant information and informative components

- Informative components have high relative entropy, relative to nominal model
- Nominal model is created as the distribution of population
- Nominal model is used to calculate the log-likelihood ratio for individual model with different dimensions



Mean relative entropy for spectrogram matrix



Equal Error Rate varies with Threshold of Informative Components Selection

Statistical models for spectrogram

- **First model used:** Exponential distribution of each time-frequency bin motivated by a modified central limit theorem [3]
- **Model with improved performance:** Log-normal model for the spectrogram
 - The parameters of Gaussian are estimated using maximum likelihood
 - A nominal model is estimated based on all training data
 - Score function is based on Euclidean distance [5]

$$S_i = \sum_{n=1, p=1}^{N, P} \left[(Y(n, p) - M_i(n, p))^2 - (Y(n, p) - M_0(n, p))^2 \right] I_{d(M_i(n, p), M_0(n, p)) > \kappa}$$

Information Fusion

Informative components

- Separate models are trained with data from different sessions
- Informative components are extracted for each model separately

Stable components

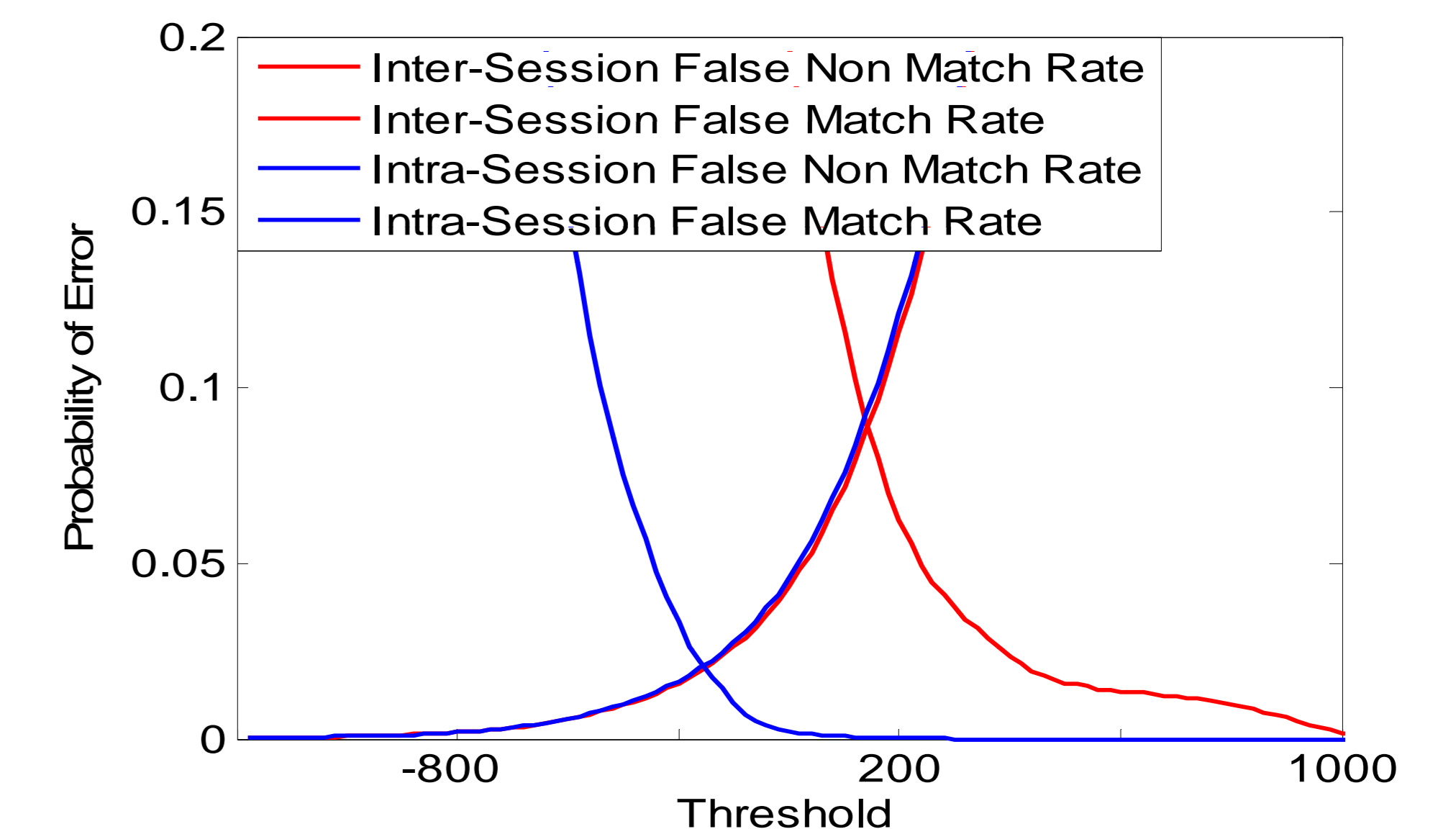
- L^1 distance between model 1 f_1 , model 2 f_2 , mixture model f_{12} and nominal model f_0 is calculated to select the stable components [5], [6]

$$\int_{-\infty}^{\infty} |f_1^{p,i} - f_2^{p,i}| d\varphi < k \int_{-\infty}^{\infty} |f_{12}^{p,i} - f_0^{p,i}| d\varphi$$

- A final log-normal model with informative and stable components is obtained

Results

- Biometric authentication performance is evaluated based on 191 subjects, over 3 sessions (each session has a time gap more than 2 weeks [5])
- Intra-session test: EER less than 1%
- Inter-session test: EER less than 9%
- Superimposed false match rate indicates the uniqueness property
- Informative and stable components preserve the permanence property



Acknowledgment

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References

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