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Real-Time Probabilistic Heart-Beat Classification and Correction for Embedded Systems

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Electrocardiogram acquisition and processing

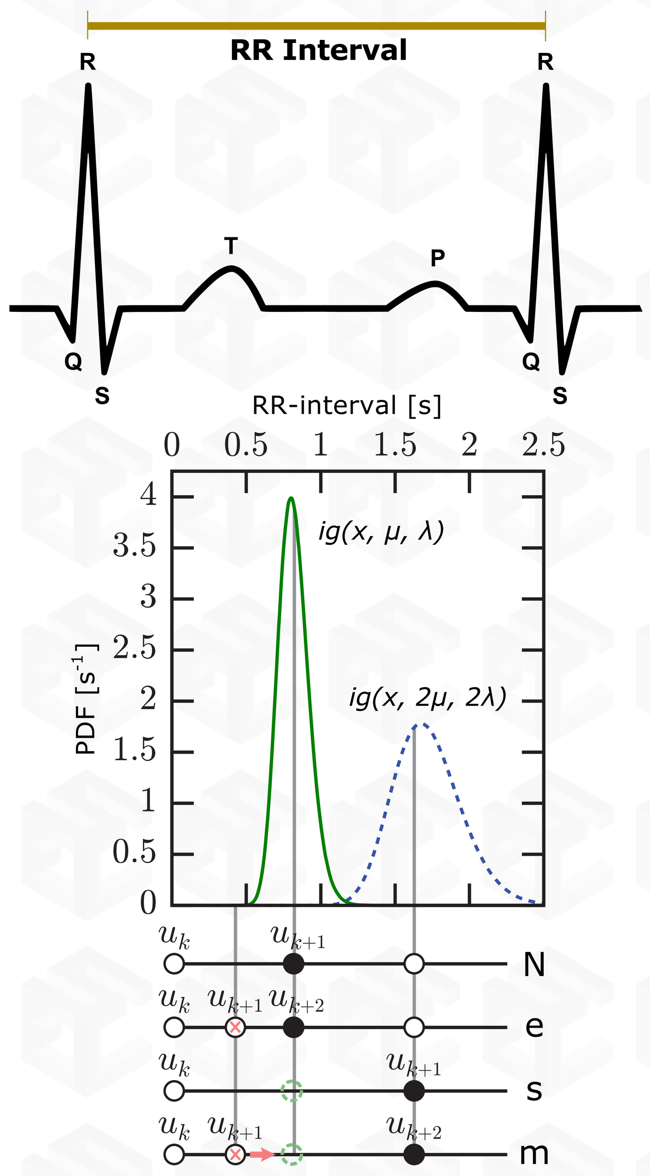
Hospital:
- \+ Good signal quality
- \+ High processing power
- \- Highly invasive (up to 12 leads)
- \- Expensive
- \- Bulky

Embedded devices:
- \- Variable signal quality (noise)
- \- Low processing power
- \+ Non-invasive
- \+ Affordable for individuals
- \+ Wearable technology

ECG delineation and analysis are performed in real-time on the device, but some algorithms are very sensitive to corrupted data

Goal: Automatic online analysis and correction of heart-beat series on an embedded platform

Probabilistic heart-beat classification

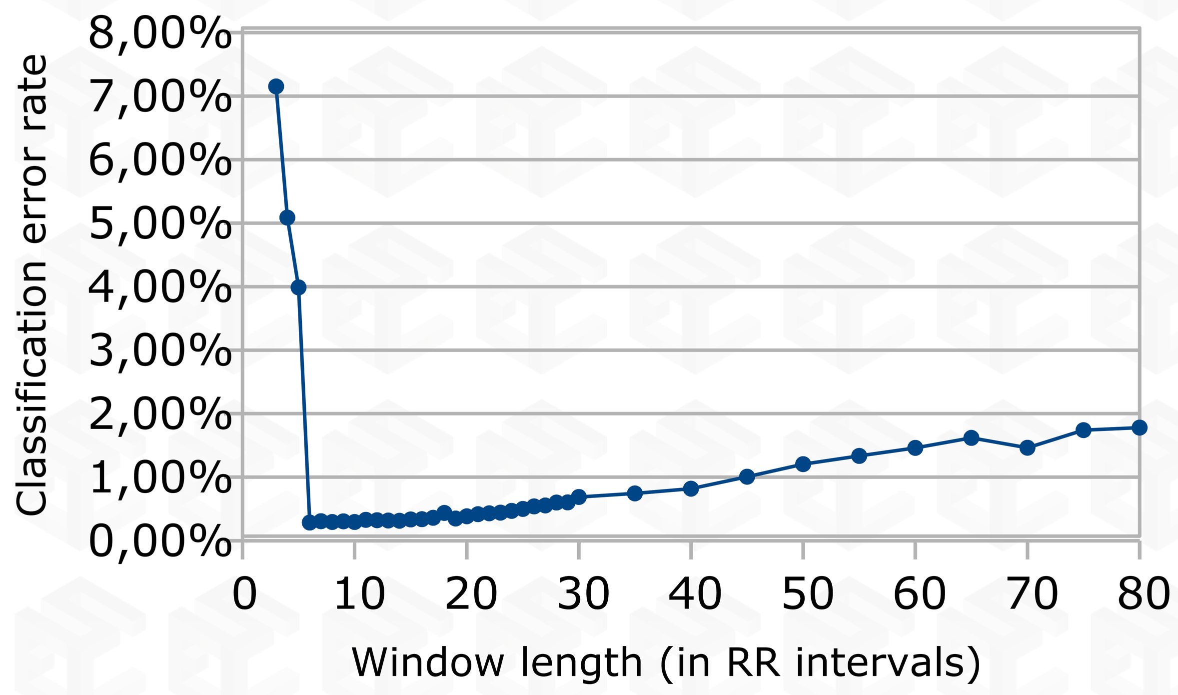


Beats modeled as probabilistic events from an Inverse Gaussian law
- Parameters μ and λ updated for each new beat k
- Beat k-1 classified and corrected as soon as beat k available

Possible outcomes for a single beat:
- Normal beat N
- Extra-beat e (*i.e.* from muscle noise)
- Skipped beat s (*i.e.* from bad contact)
- Misplaced beat m (*i.e.* ectopic beat)

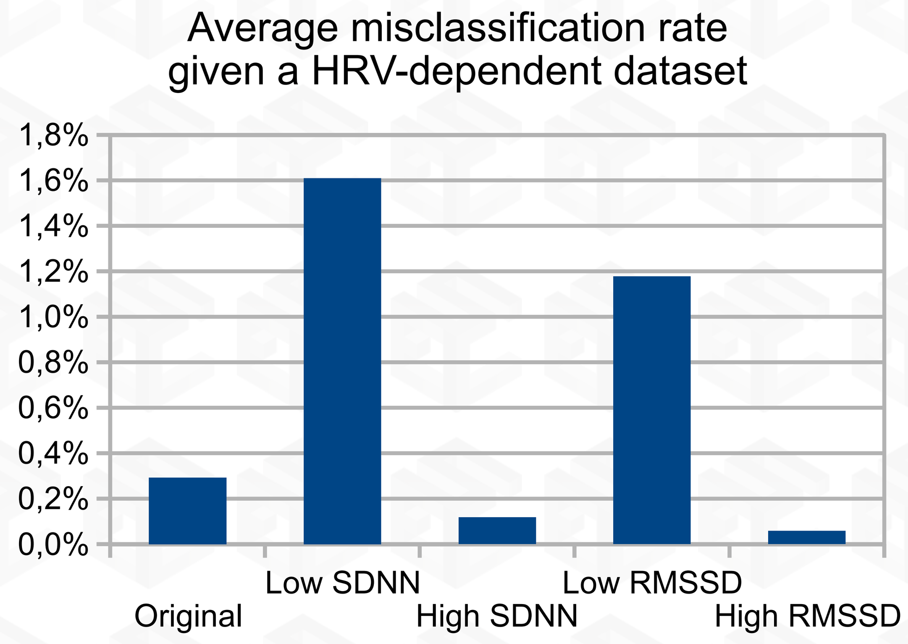
Reducing the CPU & memory load

Improvements and optimization for embedded platforms done by reducing the complexity:
- Salt-and-pepper filtering of outliers
- Processing window range reduced
- Exponential decay removed
- Alternate estimators of μ and λ



Influence of the training dataset

Results are very sensitive to training:
- The training dataset must be representative
- Relative weighting coefficient need fine-tuning



Training recordings used:
- Reference set
- Low SDNN
- High SDNN
- Low RMSSD
- High RMSSD

Performance evaluation done using the remaining files.

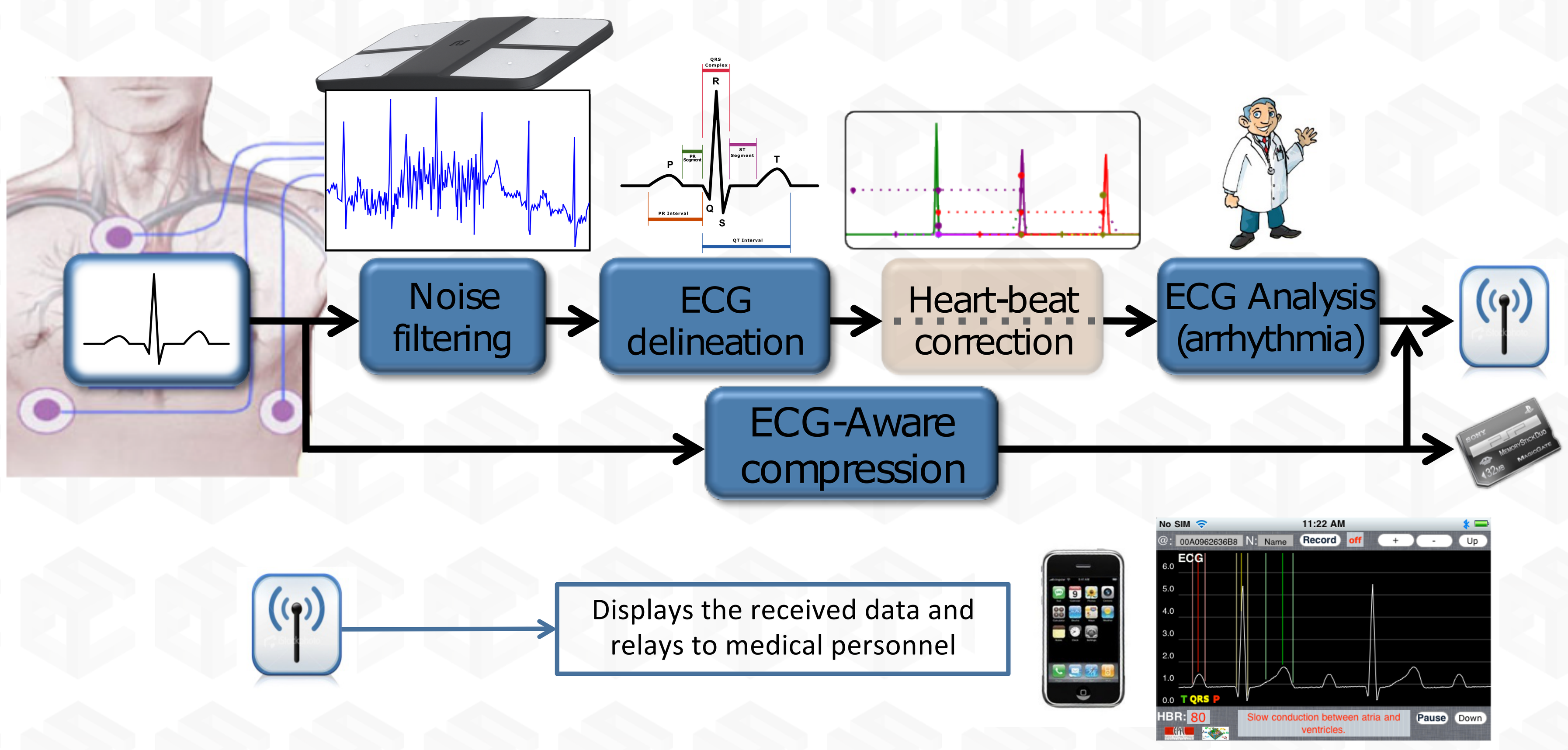
Statistical evaluation for training set:
- Random shuffling of recordings
- Training sets ranging from 10% to 90% of total dataset

⇒ Bigger datasets are more representative of HRV diversity

Integration in the processing pipeline

Several processings for HRV analysis benefit from this correction:
- Time-domain: SDNN, RMSSD
- Frequency-domain: LF/HF

⇒ Integration in the pipeline for some RR-based analysis



Results & conclusion

Confusion matrix (72504 beats, 18h of recording, 30% error rate)

		Predicted type			
		N	e	s	m
Real type	N	*50642*	1	83	30
	e	54	*7189*	0	7
	s	1	0	*7242*	3
	m	61	0	34	*7157*

Classification is right more than 99.5% of the time

Features summary:
- Recovery of highly corrupted series
- Discrimination between different situations (N, e, s, m)
- Affordable computational load for embedded systems
- Fast response to heart-rate change (narrow windowing)

⇒ Algorithms using RR-intervals in wearable devices benefit from this automatic classification and correction yielding better results