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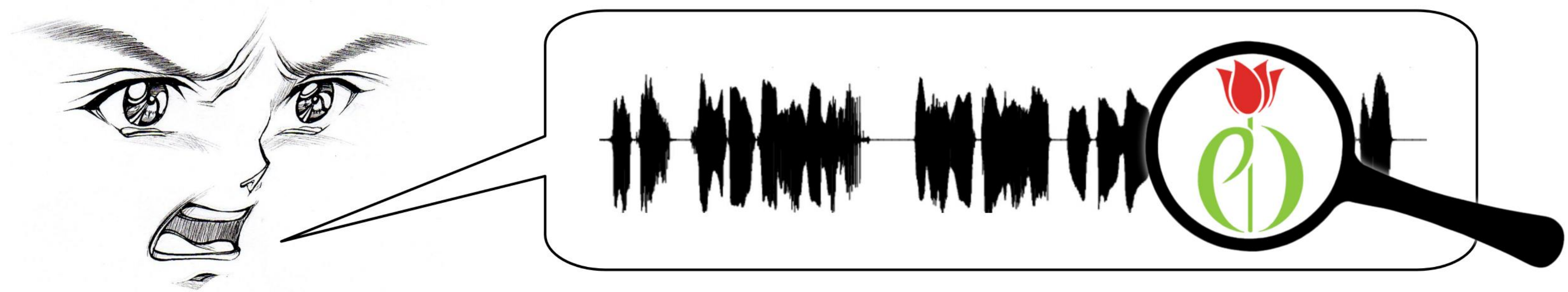

Exploiting voice signal decomposition in expert system for Parkinson's disease detection

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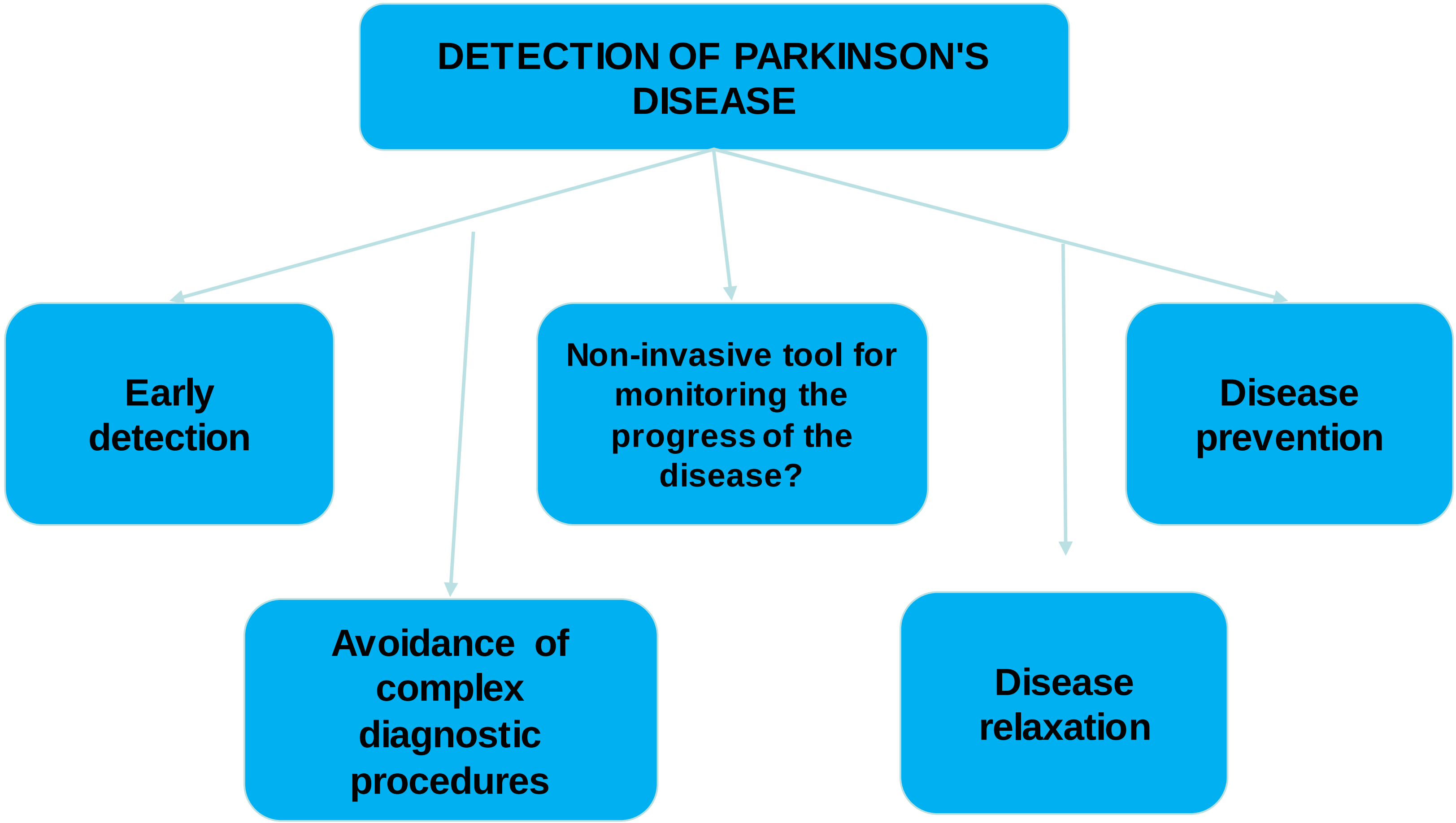
Problem, goal and keypoints of the research

- Problem
  - Parkinson's disease (PD) – the 2nd most common neurogenerative disease. Loss of dopaminergic neurons at the time of diagnosis can reach ~50% and neuroprotective strategies could be too late to slow it.
  - Speech anomalies in PD subjects can be observed ~5 years before clinical diagnosis, early objective diagnostic markers/tools are needed.
- Goal
  - Non-invasive tool for Parkinson's disease (PD) screening.
  - Medical decision support system for healthcare specialists.
    - Monitoring of PD progression, outcome of therapy or anti-PD drugs.
- Keypoints
  - Subject's data: audio signal (.wav) from acoustic cardioid microphone
    - ~3 sustained voice recordings – vowel "a" phonation at a comfortable pitch
  - Mode decomposition algorithms: empirical (EMD), variational (VMD).
  - Feature set: 12 Perceptual Linear Predictive Cepstral Coefficients
  - Random forest (RF) learner: base and meta (decision-level fusion).
  - RF variable importance from meta-learner for extra insights.
  - t-SNE on RF proximity matrix provide 2D mapping for recordings.

Problem and it‘s relevance



Research fields: voice signal analysis, pattern recognition, expert systems, computational intelligence.

Resarch object: voice recordings of healthy and Parkinson‘s disease individuals.

Related work and existing challenges

- Extensive overview – Orozco-Arroyave et al. 2016:
  - Orozco-Arroyave JR, Hönig F, Arias-Londono JD, Vargas-Bonilla JF, Daqrouq K, Skodda S, Rusz J, Nöth E (2016) **Automatic detection of Parkinson's disease in running speech spoken in three different languages**. *The Journal of the Acoustical Society of America* 139(1):481–500. doi:10.1121/1.4939739
  - recommends splitting speech into voiced / unvoiced parts

- Existing challenges in the related work:
  - Size of database is a major problem → unreliable estimates.
    - biggest database so far – 88 PD and 88 HC German subjects
  - Reported researches often lack proper* validation scheme.
    - *proper: leave-one-subject-out (or leave-one-individual-out)
  - Main emphasis on the extraction of various audio features.
  - Interspeech 2015 computational paralinguistics challenge !

Summary of the LUHS voice database

Recordings	Parkinson (PD)	Healthy (HC)	Total
Male	36 (107)	105 (312)	141 (419)
Female	39 (116)	203 (599)	242 (715)
Total:	**75 (223)**	**308 (911)**	383 (1134)

- Numbers denote amount of subjects (recordings):
  - PD – Parkinson’s disease patients
  - HC – healthy control subjects

- Recorded at: Department of Otorhinolarynology, Lithuanian University of Health Sciences (LUHS), Kaunas, Lithuania
- Microphone: AKG Perception 220 acoustic cardioid

Research methodology

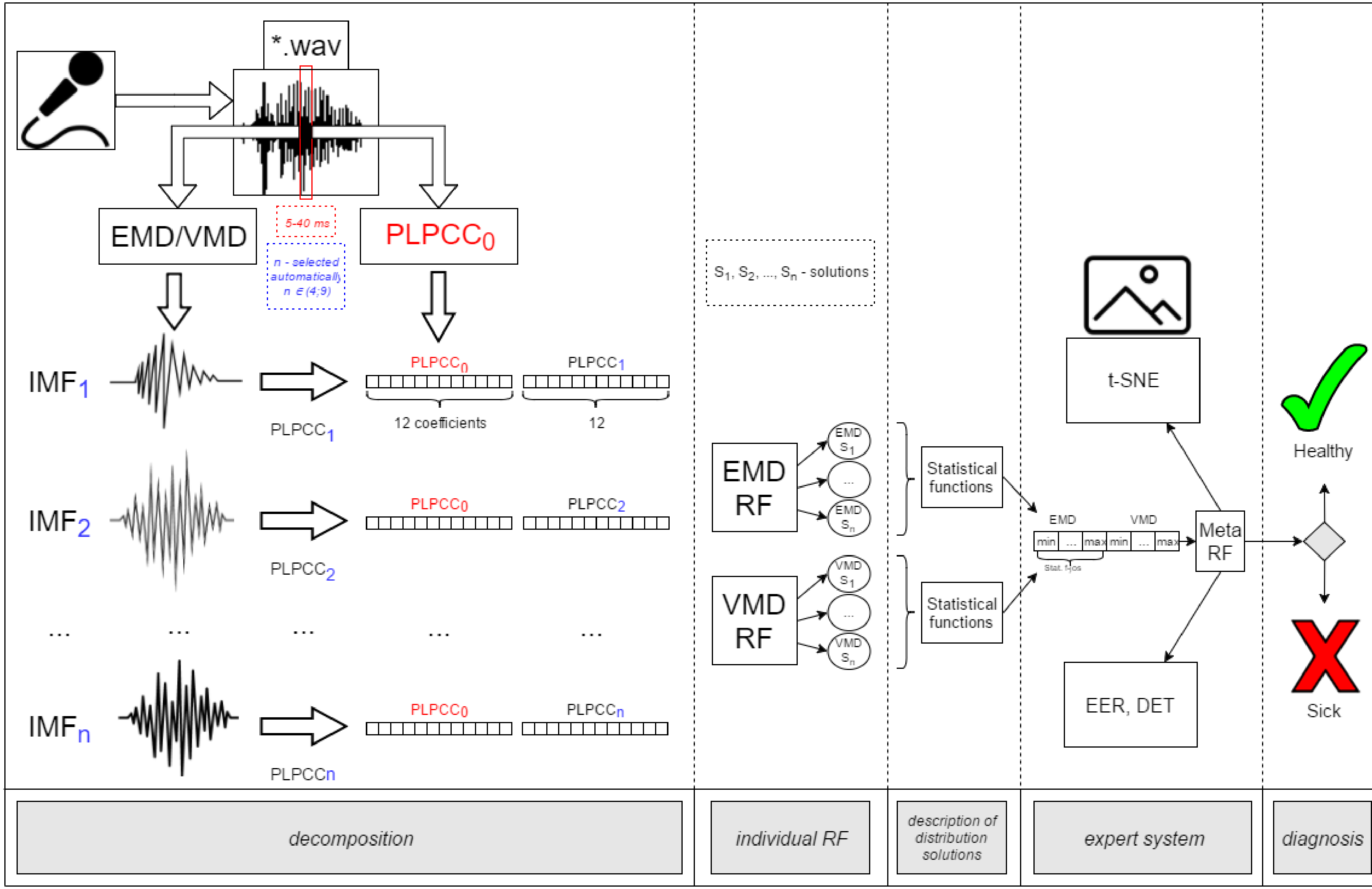
1. Statistical functions	2. Features	3. Detection	4. Validation	5. Prototype

• min / max
• mean
• median
• trimean
• std,
• IQR quartiles
• skewness
• kurtosis.
	• Decomposition:
	  • EMD → IMFs
	  • VMD → IMFs
	• Feature extraction
	  • PLPCC
		• Random forest
		• Ensemble of RFs
		  • base-RF
		  • meta-RF
			• RF out-of-bag
			• Equal error rate
			• Vizualization of proximity matrix from RF by t-SNE
			• Variable improtance
				• Service requirements
				• Prototype specification
				• Applicable technologies

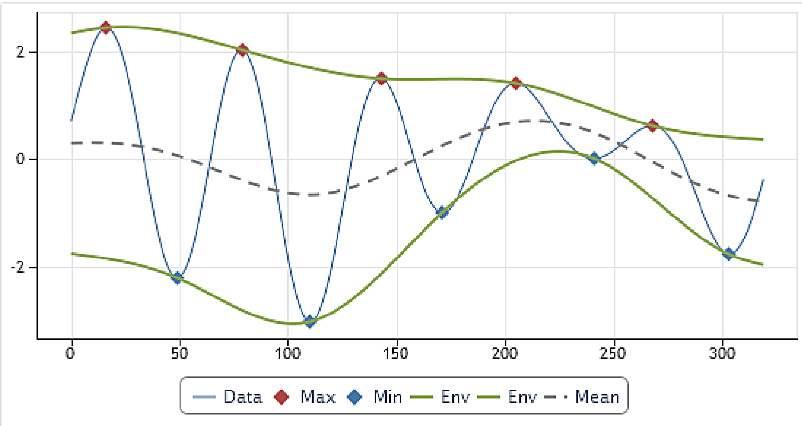
Explanation:

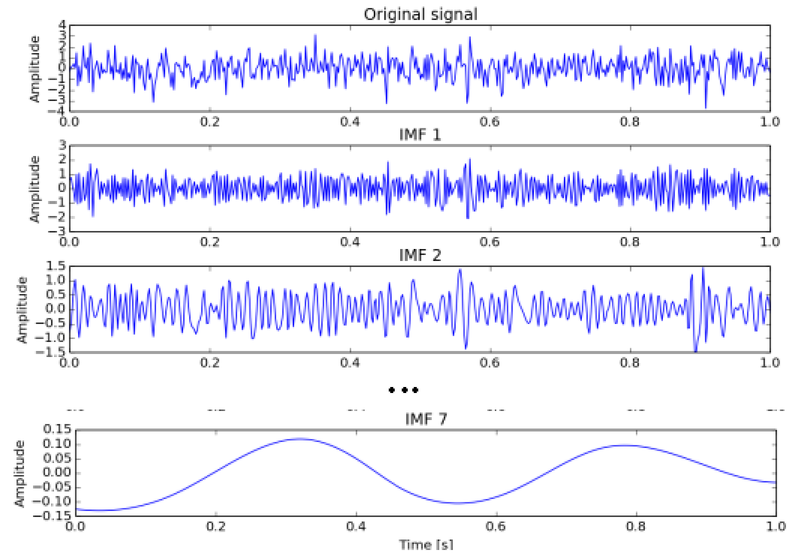
1. Statistical functions are used to compress:
   - (baseline) frame-based PLPCC features from all windows
   - (proposed) base-RF decisions from of all IMF components
2. PLPCC features are calculated for each IMF from decomposition
3. Random forest for Parkinson's disease detection
4. Evaluation of goodness-of-detection
5. Medical decision system prototype

Proposed solution: signal mode decomposition



Mode decomposition techniques considered

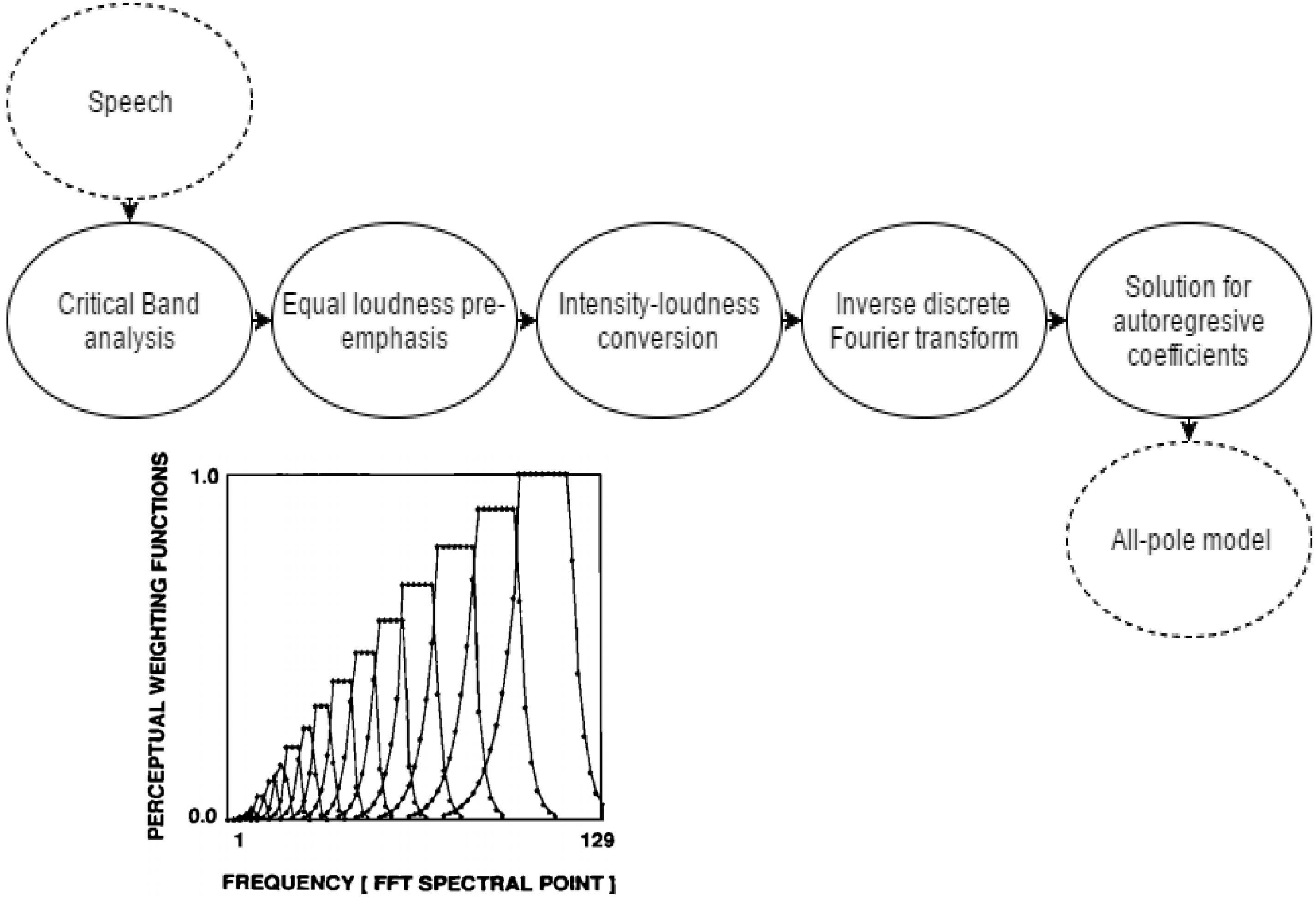




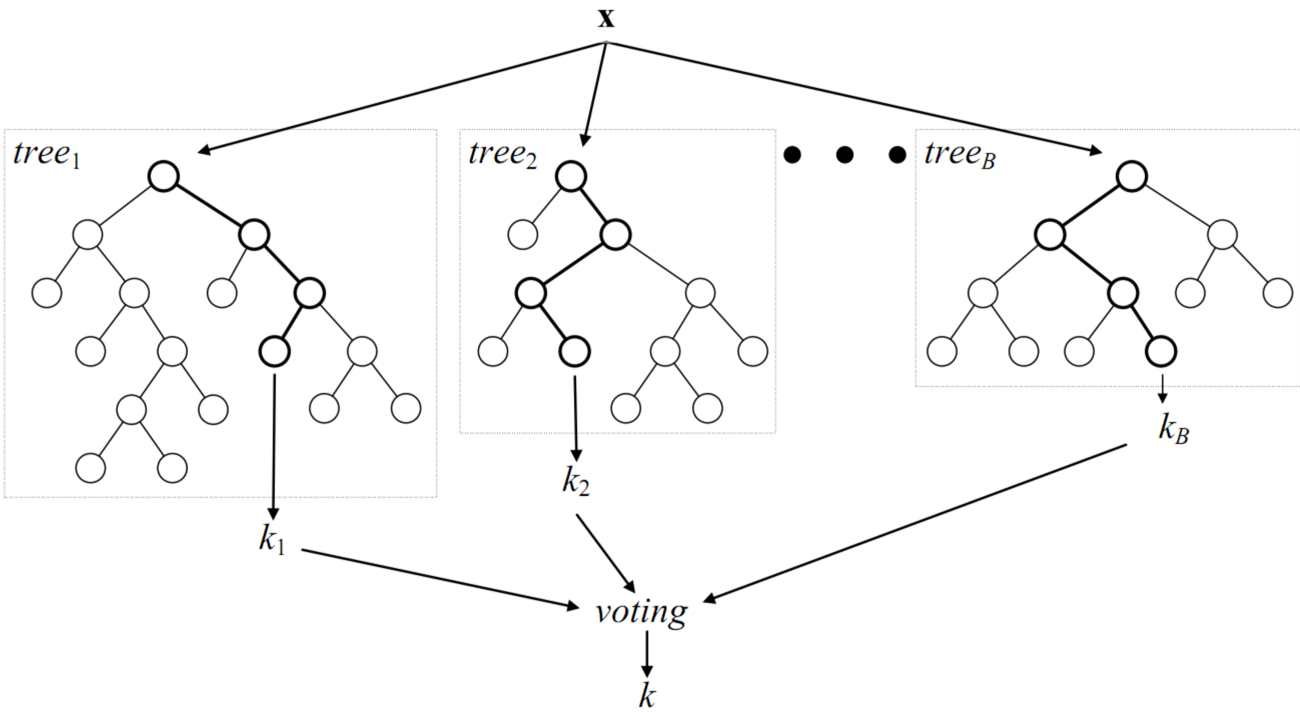
- empirical mode decomposition (EMD) – automatic number of IMFs
  - Torres ME, Colominas MA, Schlotthauer G (2011) **A complete Ensemble Empirical Mode decomposition with adaptive noise**. Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 4144-4147.
- variational model decomposition (VMD)
  - Dragomiretskiy K, Zosso D (2014) **Variational Mode Decomposition**. IEEE Transactions on Signal Processing, 62(3), 531–544.

Perceptual Linear Predictive Cepstral Coefficients

- compact “frequency signature” (Hermansky, 1990)
- alternative to Mel-Frequency Cepstral Coefficients



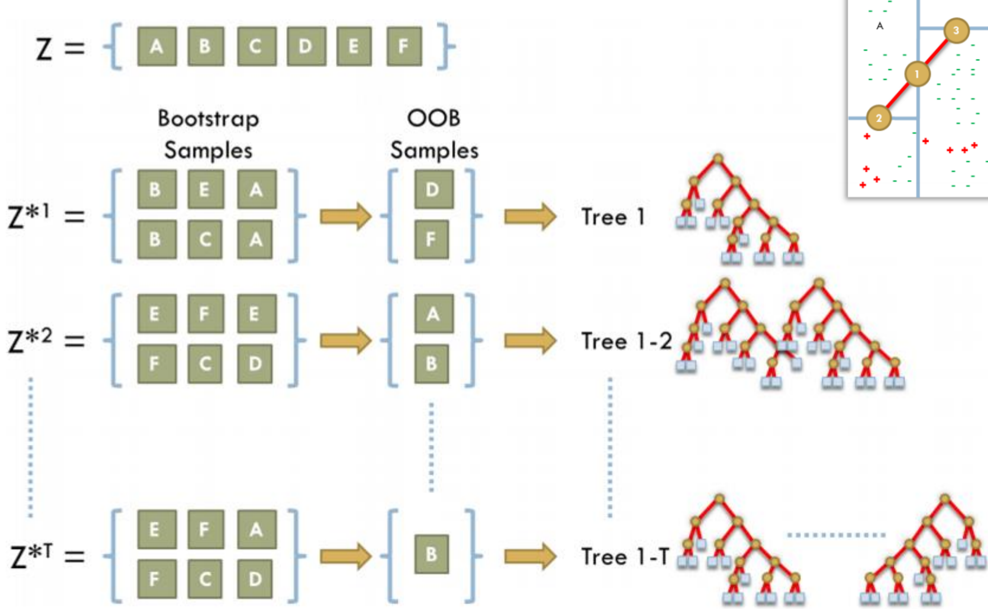
Detector – random forest (RF) (Breiman, 2001)

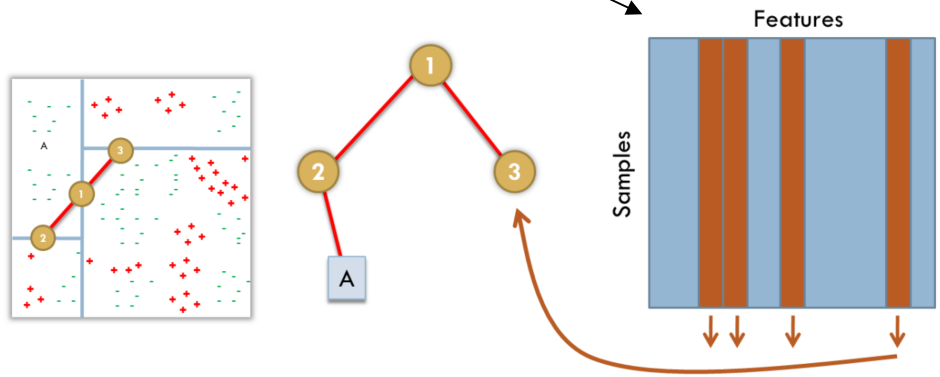


- RF is a committee of classification and regression trees (CART). Final decision *k* is derived by majority voting.
  - B (number of trees in the forest) = 5000
  - mtry (number of features for each node) = $\sqrt{p}$, $2\cdot\sqrt{p}$, $\frac{1}{2}\cdot p$
    - *p* – dimensionality of the object **x** (size of the feature vector)
- 2D map: proximity matrix → distance matrix → t-SNE

RF – ensemble of unpruned CART trees

- efficient and robust against over-fitting
  - features out-of-bag (OOB) validation - no k-fold CV needed
  - computes proximity matrix (~ similarity between recordings)
  - bootstrap aggregating + random subspace
    (instance bagging + feature bagging)





Decision-level fusion: base-RFs by meta-RF

- Base-learner RF is decomposition- and window-specific.
- Meta-learner RF combines decisions from base RFs.
- Input to the meta-learner is the difference between class posteriori probabilities obtained from the base-learner:

$$d(\{t_1, ..., t_L\}, \mathbf{x}) = \frac{\sum_{i=1}^{L} f(t_i, \mathbf{x}, c=2)}{L} - \frac{\sum_{i=1}^{L} f(t_i, \mathbf{x}, c=1)}{L}$$

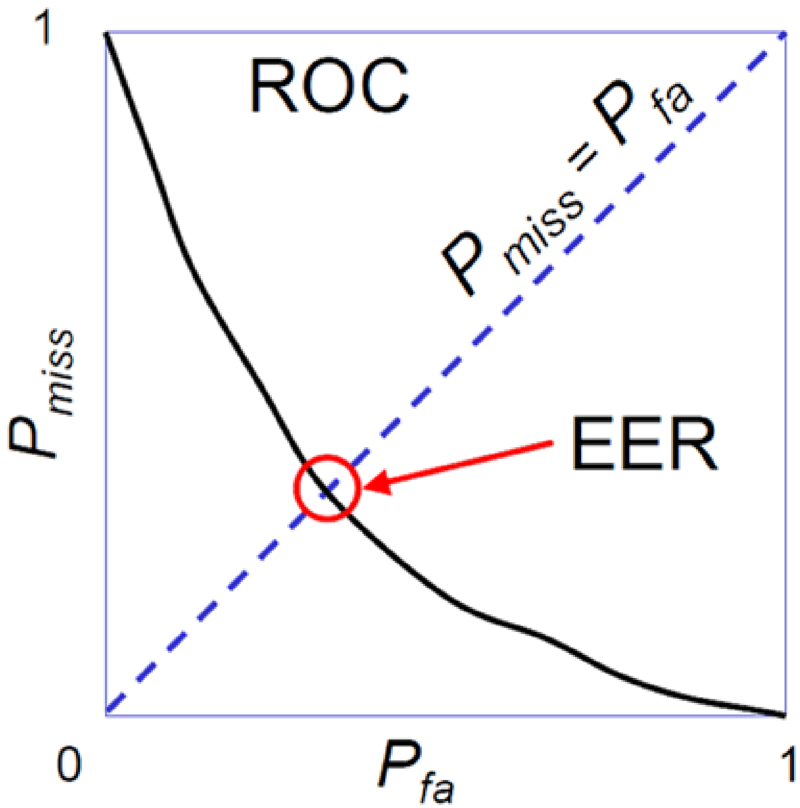
  - **x** – object being classified, L – number of trees $t_1,..t_L$ in the base RF for which object **x** is OOB, *c* is class label (1 – HC, 2 – PD)
  - f(t_i, **x**, *c*) stands for the *c*-th class frequency in the leaf node, into which **x** falls in the *i*-th tree t_i of the base RF:

$$f(t_i, \mathbf{x}, c) = \frac{n(t_i, \mathbf{x}, c)}{\sum_{j=1}^{C} n(t_i, \mathbf{x}, c_j)}$$

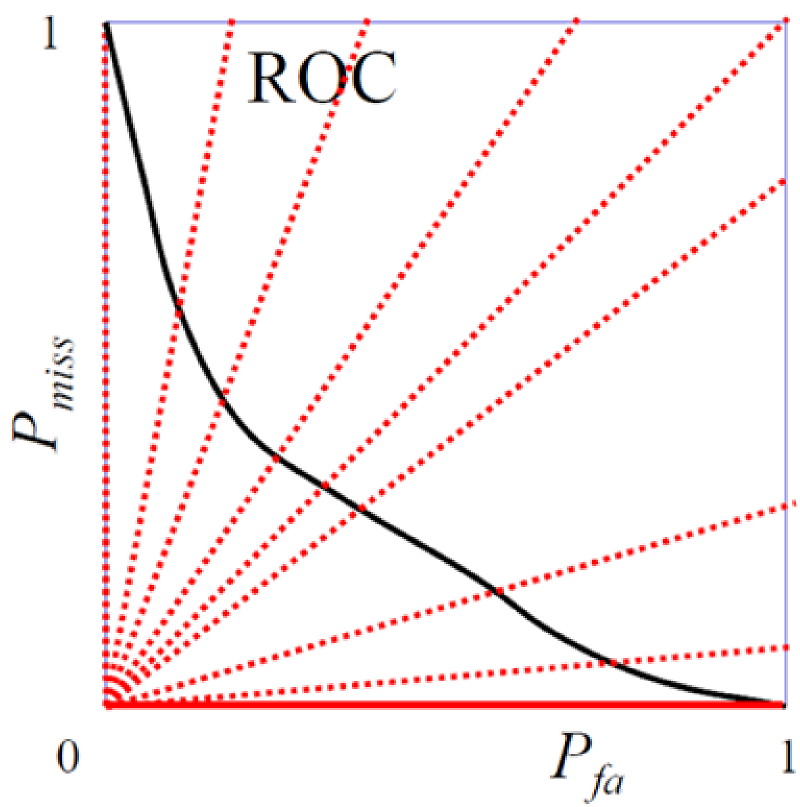
  - *C* – number of classes, n(t_i, **x**, *c*) – number of training data from class *c* falling into the same leaf node of t_i as **x**

Measuring the goodness of detection

- EER = [0 .. 50 .. 100%]
  - *equal error rate*
- ROC (DET) crosses diagonal
  - or sensitivity = specificity
  - or miss rate = false alarm



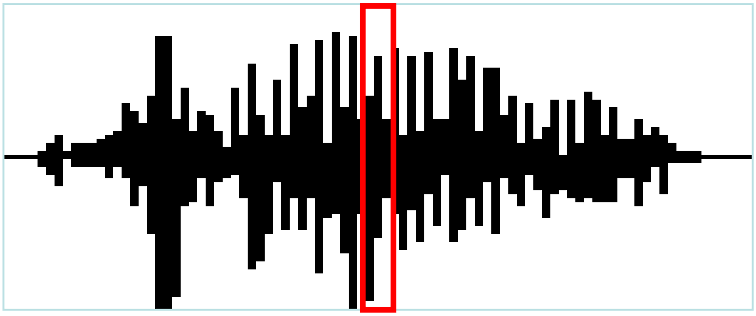
- C_{llr} = [0 .. $\log_2 N$ .. ∞]
  - *cost of log-likelihood-ratio*
  - *~ multi-class cross-entropy*
- integral of ROC curve & costs & class priors (universal measure)



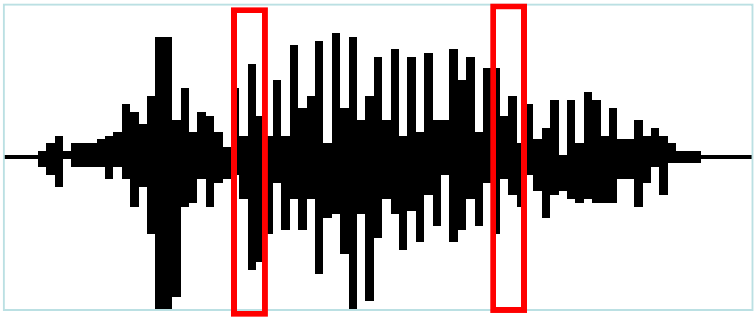
Experimental setup: windowing scheme

Window size (0.01 – 0.10 s)

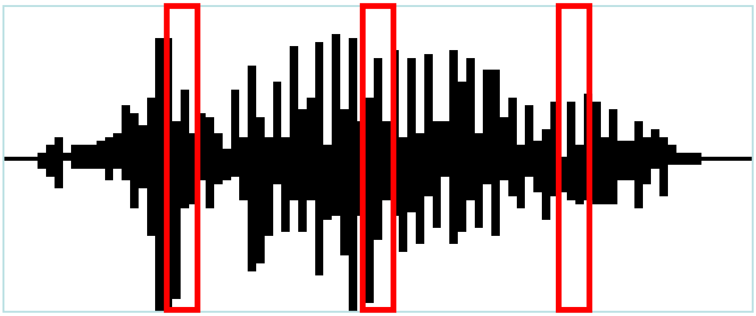
1 window



2 windows



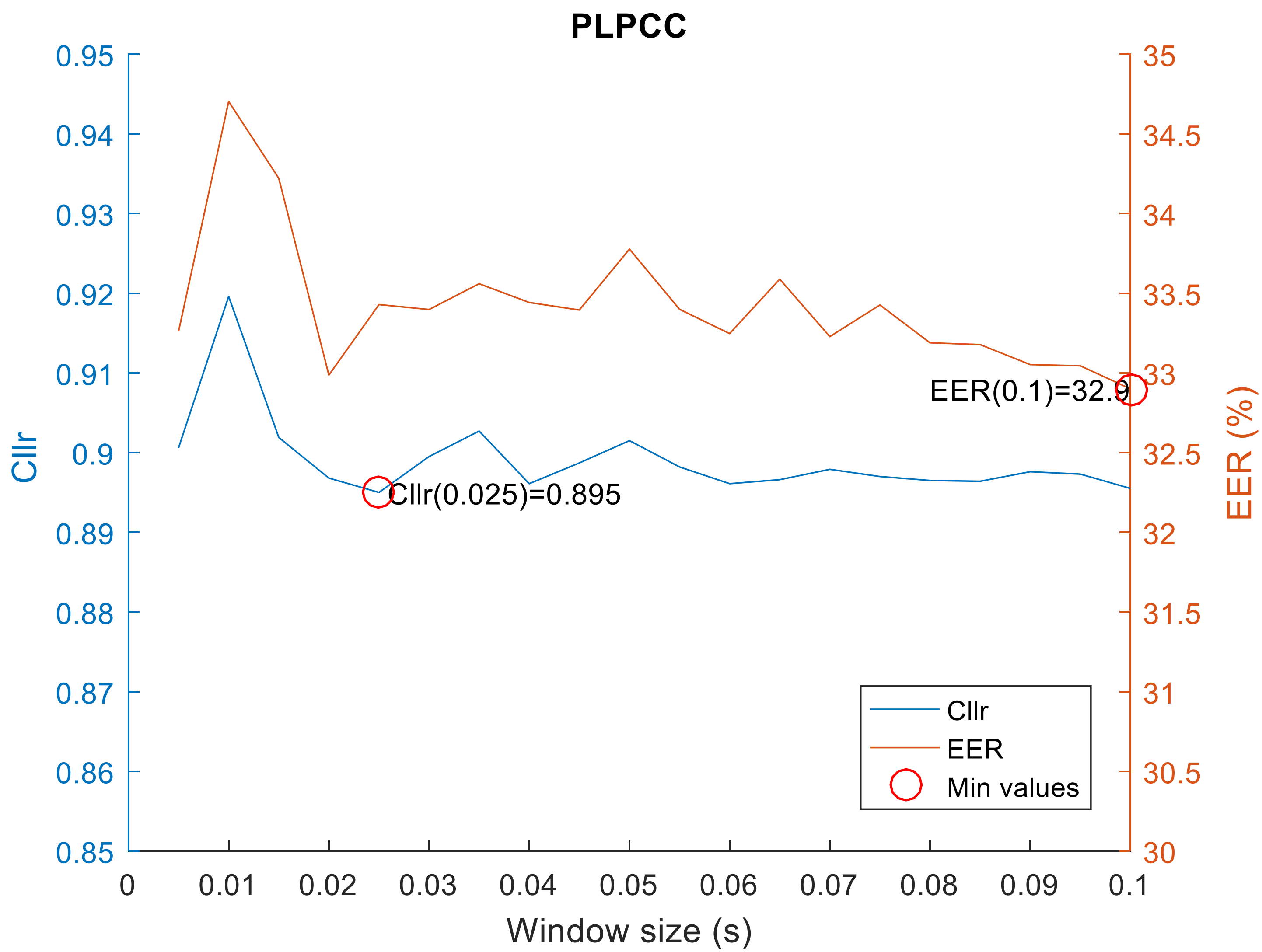
3 windows



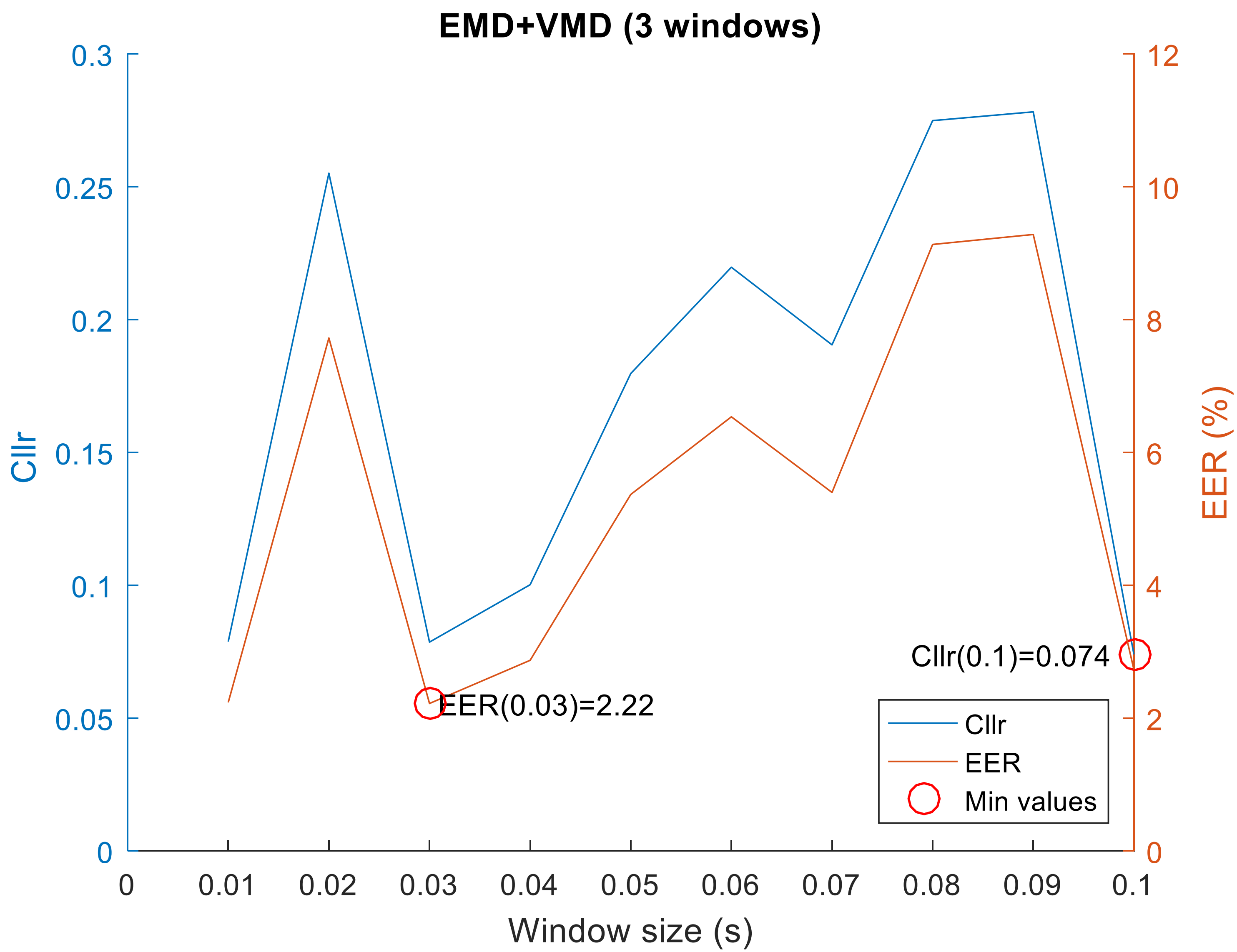
Experimental results: window size and quantity

Size (s)	Quantity	Type of decomposition used in decision-level fusion					
		EMD		*VMD*		*EMD+VMD*	
		Cllr	*EER*	*Cllr*	*EER*	*Cllr*	*EER*
0.01	1	0.718	26.23	0.237	6.65	0.215	6.10
	2	0.617	20.83	0.754	26.20	0.565	19.12
	3	0.115	3.03	0.245	6.71	0.079	2.24
0.02	1	0.448	13.96	0.682	23.03	0.375	12.42
	2	0.385	13.08	0.610	20.32	0.336	10.45
	3	0.321	9.70	0.499	16.66	0.255	7.72
0.03	1	0.456	13.92	***0.100***	***2.65***	0.085	***2.22***
	2	0.306	10.07	0.503	14.95	0.264	8.27
	3	0.342	11.32	0.115	3.33	0.079	***2.22***
0.04	1	0.419	11.77	0.586	19.08	0.359	11.51
	2	0.379	11.69	0.541	17.01	0.313	10.05
	3	***0.010***	***2.90***	0.451	13.70	0.100	2.87
0.05	1	0.355	10.71	0.583	19.02	0.303	8.53
	2	0.347	10.92	0.539	16.67	0.300	9.73
	3	0.216	5.80	0.449	13.36	0.180	5.37
0.06	1	0.316	10.08	0.555	17.16	0.266	7.88
	2	0.328	10.07	0.441	14.23	0.265	8.41
	3	0.244	7.39	0.419	13.24	0.220	6.54
0.07	1	0.405	11.84	0.561	17.15	0.349	10.61
	2	0.450	14.68	0.474	15.48	0.380	12.73
	3	0.236	6.07	0.356	12.15	0.190	5.40
0.08	1	0.379	12.09	0.529	16.85	0.309	9.93
	2	0.323	11.27	0.505	15.91	0.288	9.78
	3	0.297	9.87	0.448	14.11	0.275	9.13
0.09	1	0.443	13.34	0.591	19.59	0.368	11.24
	2	0.349	10.56	0.504	16.10	0.307	9.84
	3	0.317	10.11	0.458	13.90	0.278	9.28
0.10	1	0.363	10.78	0.495	16.21	0.252	7.66
	2	0.390	12.17	0.509	15.64	0.359	12.07
	3	0.254	7.21	0.109	3.86	***0.074***	2.73

Experimental results – baseline solution

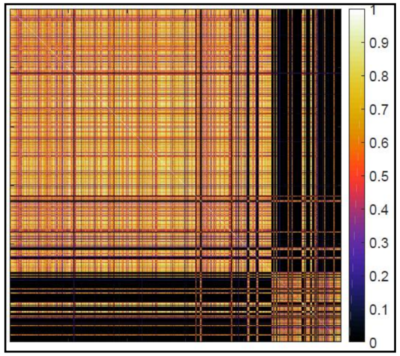


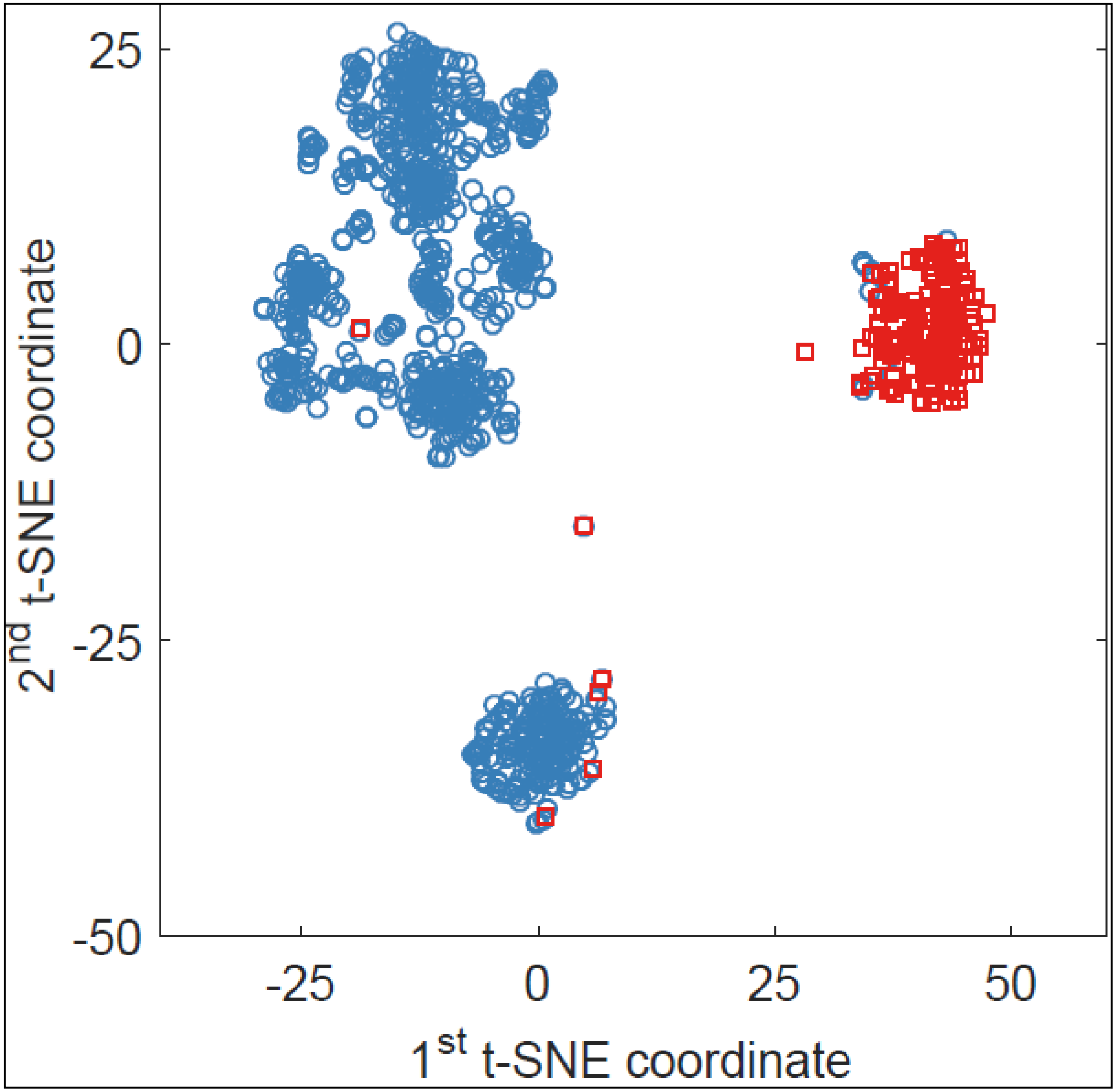
Experimental results – proposed solution



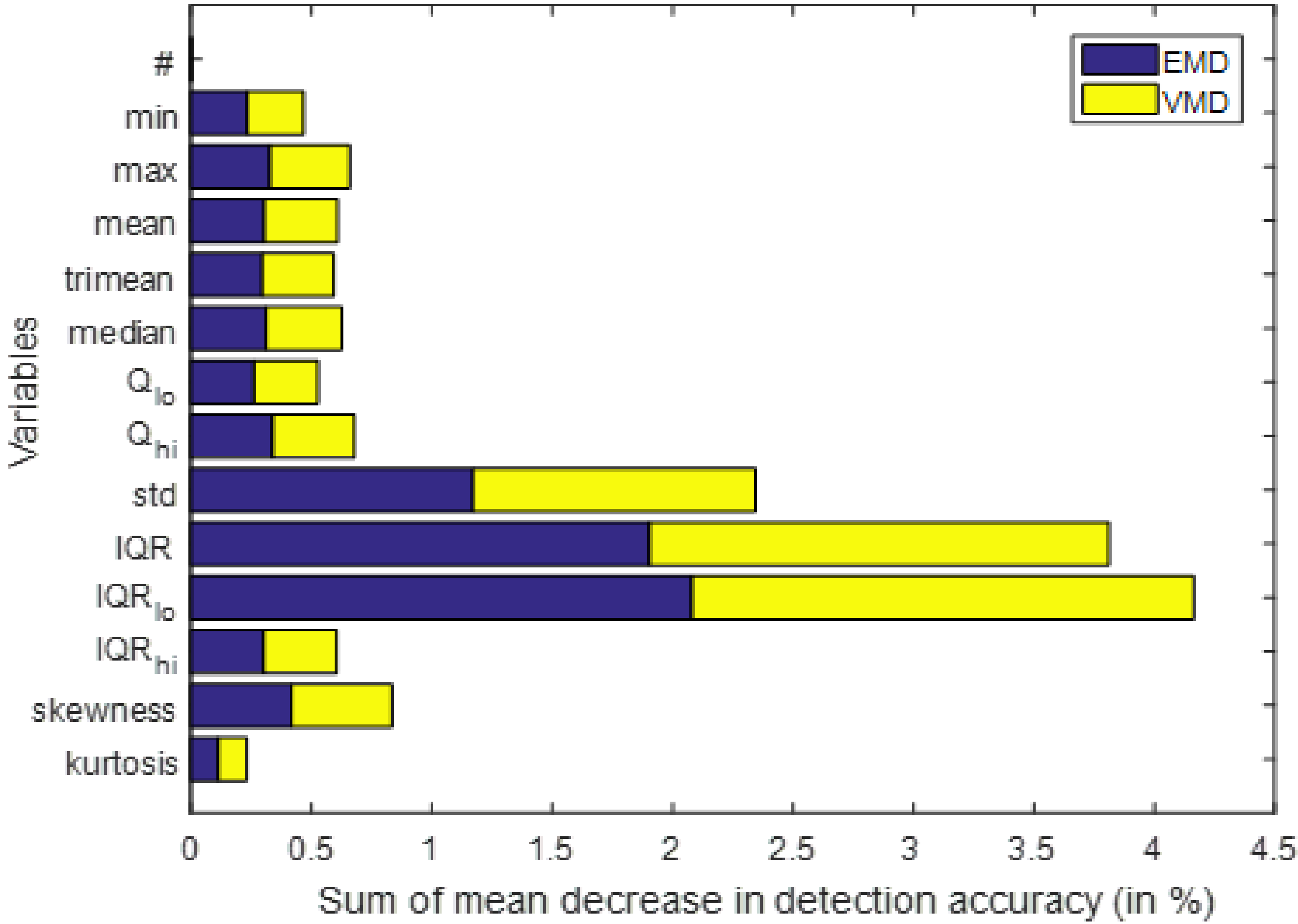
Medical decision support by visualization

- meta-RF proximity matrix → t-SNE → 2D map of .wavs



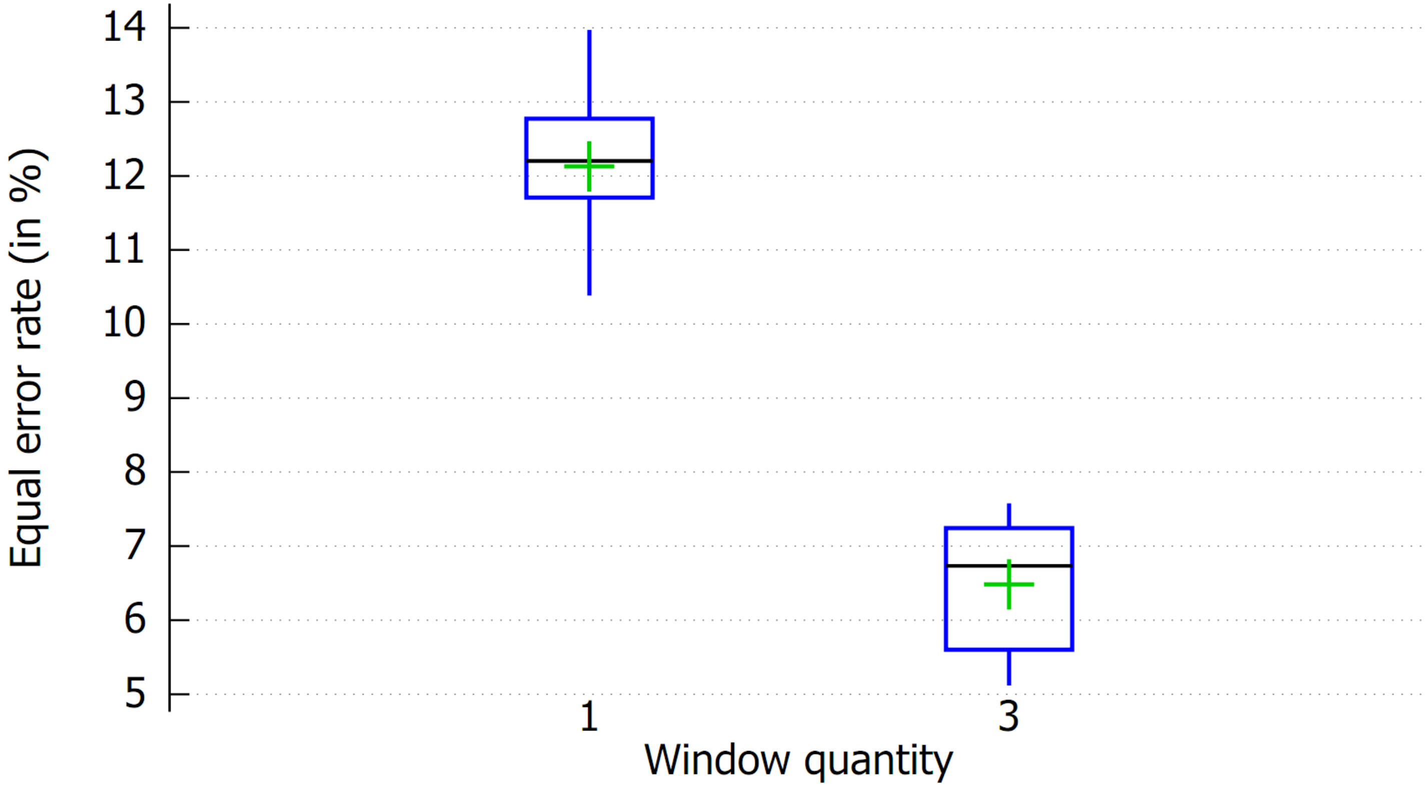


Variable importance from meta-RF



Sensitivity analysis – repeated detections

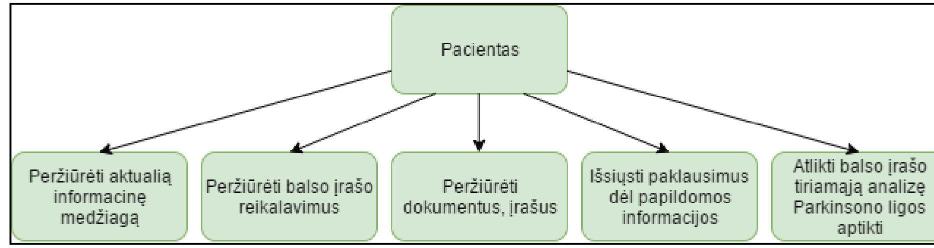
- (5 EMD+VMD runs) × (5 base-RF) × (5 meta-RF) = 125
- medians are significantly different by Wilcoxon rank-sum

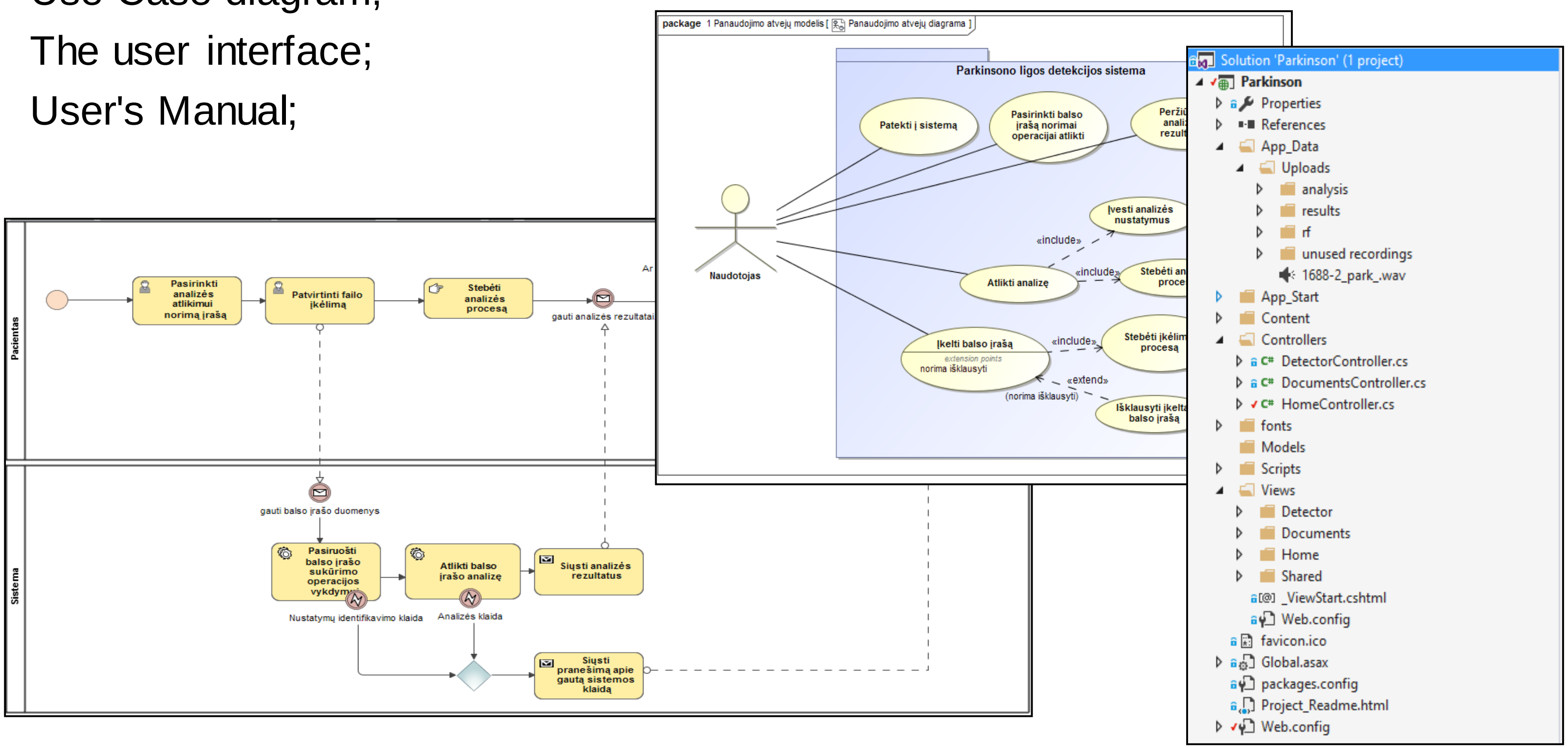


	mean	min	Q1	median	Q3	max
1	**12.129**	10.386	11.708	**12.203**	12.772	13.972
3	**6.4818**	5.1183	5.6006	**6.7329**	7.2433	7.5783

Designing expert system prototype

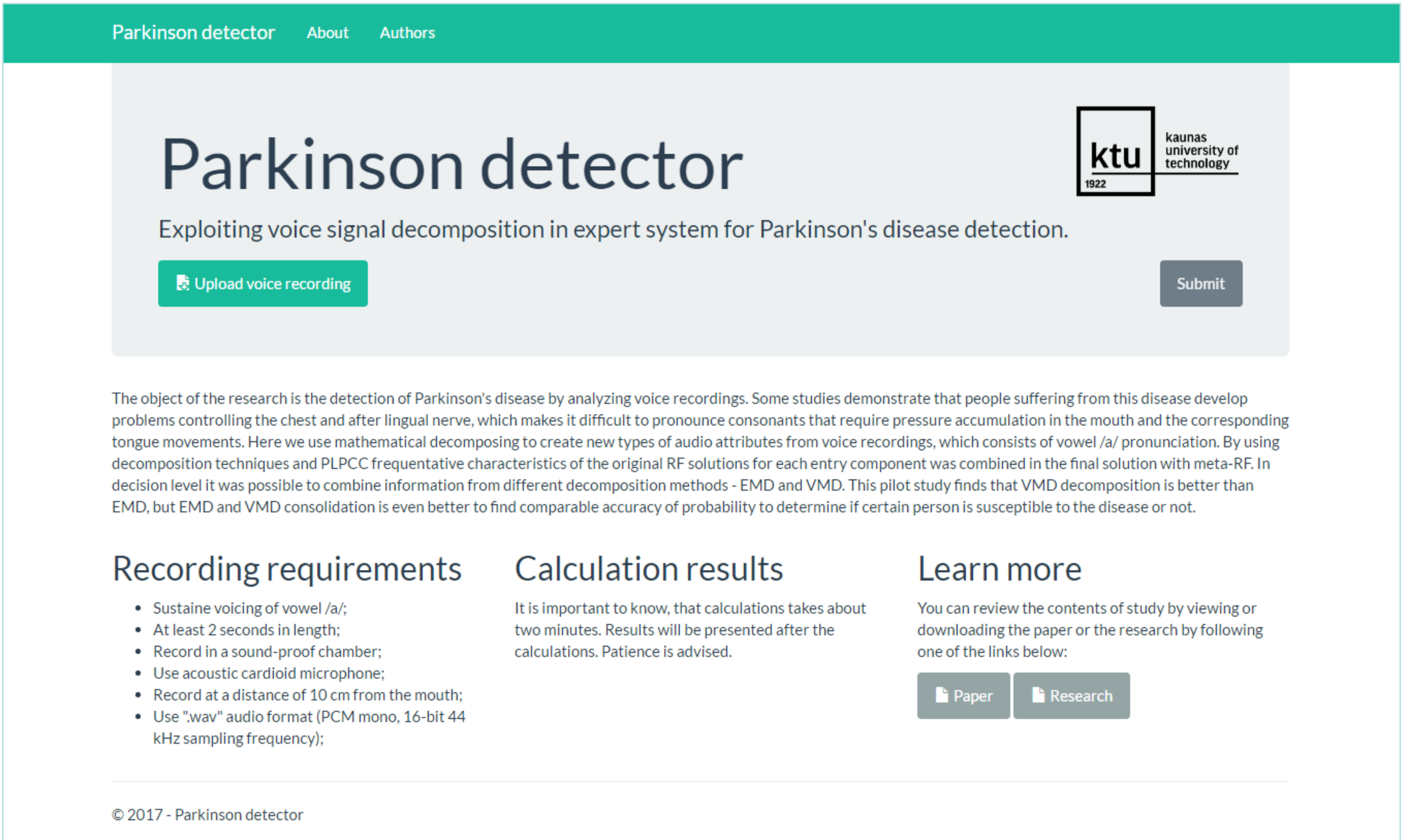
- Product definition, system limitations;
- Functional and non-functional requirements;
- Hierarchy chart;
- Technical specifications;
- The logical architecture;
- The business logic;
- Use Case diagram;
- The user interface;
- User's Manual;





Graphical user interface for expert system

- web-based solution to upload .wav and obtain diagnosis



Conclusions and future work

- Detection performance:
  - (baseline, without decomposition) best EER = ~33%
  - (proposed, 1 window of 30 ms) mean EER = ~12.1%
  - (proposed, 3 windows of 30 ms) mean EER = ~6.5%
- Fusion of 3 windows and EMD+VMD is recommended.
- Both decompositions are useful, VMD better than EMD.
- Variability-related statistics most important for meta-RF.

- Future work:
  - repeated mode decomposition due to numerical instability
    - base-RF would be trained on more IMF components
    - meta-RF would be enriched by more robust statistics
  - test with recordings done using smartphone microphone
  - test expert system with another voice database (mPower)