

Measurements of physiological signals are exposed to various external disturbances, specifically during the recording of photoplethysmogram, ECG and respiration. The reasons of noise and artifacts are diverse, e.g. poor contact between sensor and body, power line interference, physical activity or cable rupture to name but a few. These artifacts can cause many false alarms during continuous long-term monitoring and could annoy and mislead medical doctors in the intensive care unit for instance. To avoid such situations, well defined and robust methods can help to reduce noise or to improve the further processing of the raw data. In this regard PhysioNet and Computing in Cardiology arranged a competition in 2014 to detect heart beats in a robust way by using multiple simultaneous measured signals⁷. In light of this, I am going to analyze the robustness against noise of selected challenge algorithms.

Best performing algorithms

- Open source code of the challenge participants taken from challenge 2014 website.
- Ranked list of competitors with performance (sensitivity SE, positive predictive value +P).
- The overall score is calculated by averaging gross sensitivity, gross positive predictivity, average sensitivity, and average positive predictivity⁷.
- Urška Pangerc et al.¹ ranked as best with an overall score of 93.64. With short distance, a cluster of well performing algorithms follows.
- The 210 records used for external evaluation consists of 152,478 heart beats and included roughly 5% abnormal beats (more details in Silva et al.⁷).

Heart Beat Detectors

PhysioNet/CinC Challenge 2014 post-phase results on the revised hidden test set (Score) and on training data sets set-p and set-p2 (SE/+P).

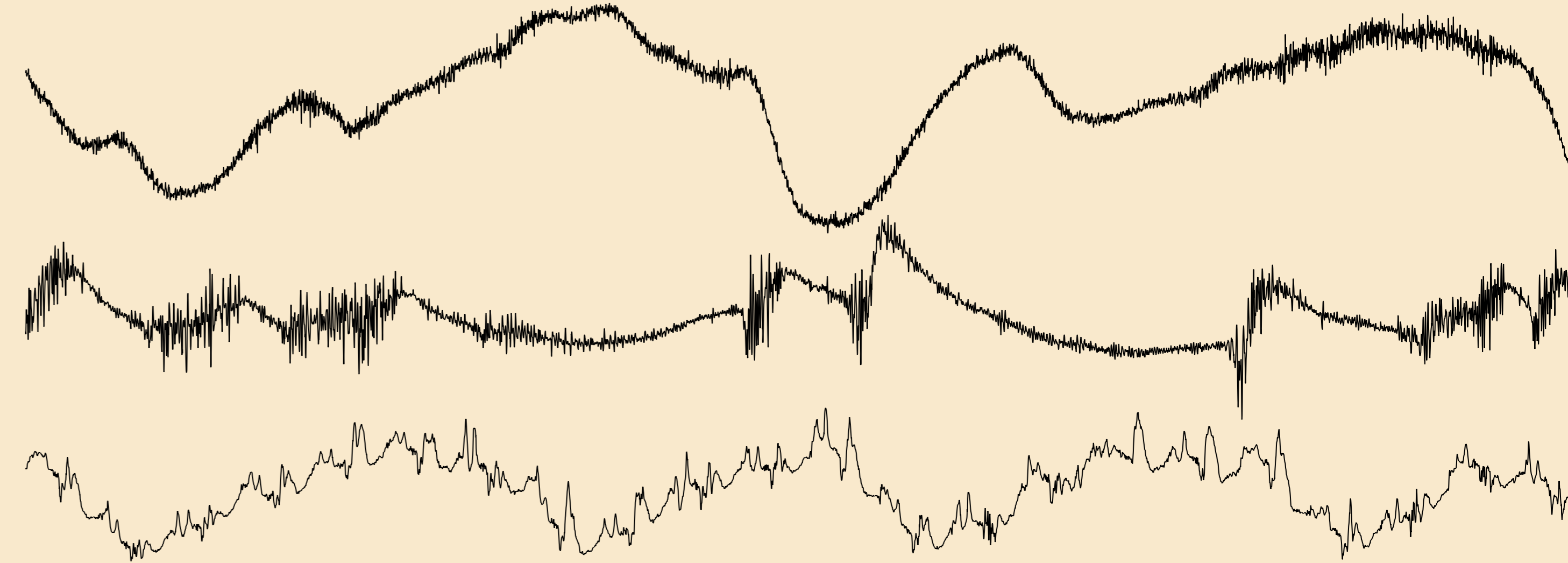
Rank	Version	Score	Reference	challenge/set-p	challenge/set-p2
1	urska.pangerc-420.zip	93.64	Pangerc et al. ¹	99.97/99.95	96.32/95.39
2	alistairewj-425.zip	91.50	Johnson et al. ²	99.82/99.80	93.68/88.37
3	hoog.antink-407.zip	90.70	Hoog Antink et al. ³	99.96/99.96	90.51/90.38
4	thomas.decooman-420.zip	90.02	de Cooman et al. ⁴	99.86/99.92	87.56/85.75
5	lj-405.tar.gz	89.73	Galeotti et al. ⁵	NA	NA
6	marcus.vollmer-402.zip	89.55	Vollmer ⁶	99.97/99.99	91.80/91.34

The noise stress test

- MIT-BIH Noise Stress Test Database⁸(NSTDB) was generated using two clean recordings (118 and 119) from the MIT-BIH Arrhythmia Database.
- The provided noisy records derived from an active measurement contains baseline wander, electrode motion artifacts and muscular noise.
- More variety of ECGs and the composition of biosignals by generating noisy records by applying WFDB-Toolbox function⁹ `nst` to the 100 clean records of the set-p training database for which all the selected algorithms shows a nearly perfect annotation.
- Noise was added in standard settings to the 10-minute records from the fifth to seventh minute and ninth to tenth minute. The clean segment till the fifth minute can be considered as a learning period.

Realistic Noise

Top: Baseline wander.
Middle: Muscle noise.
Bottom: Electrode motion artifact with baseline wander and muscle noise.



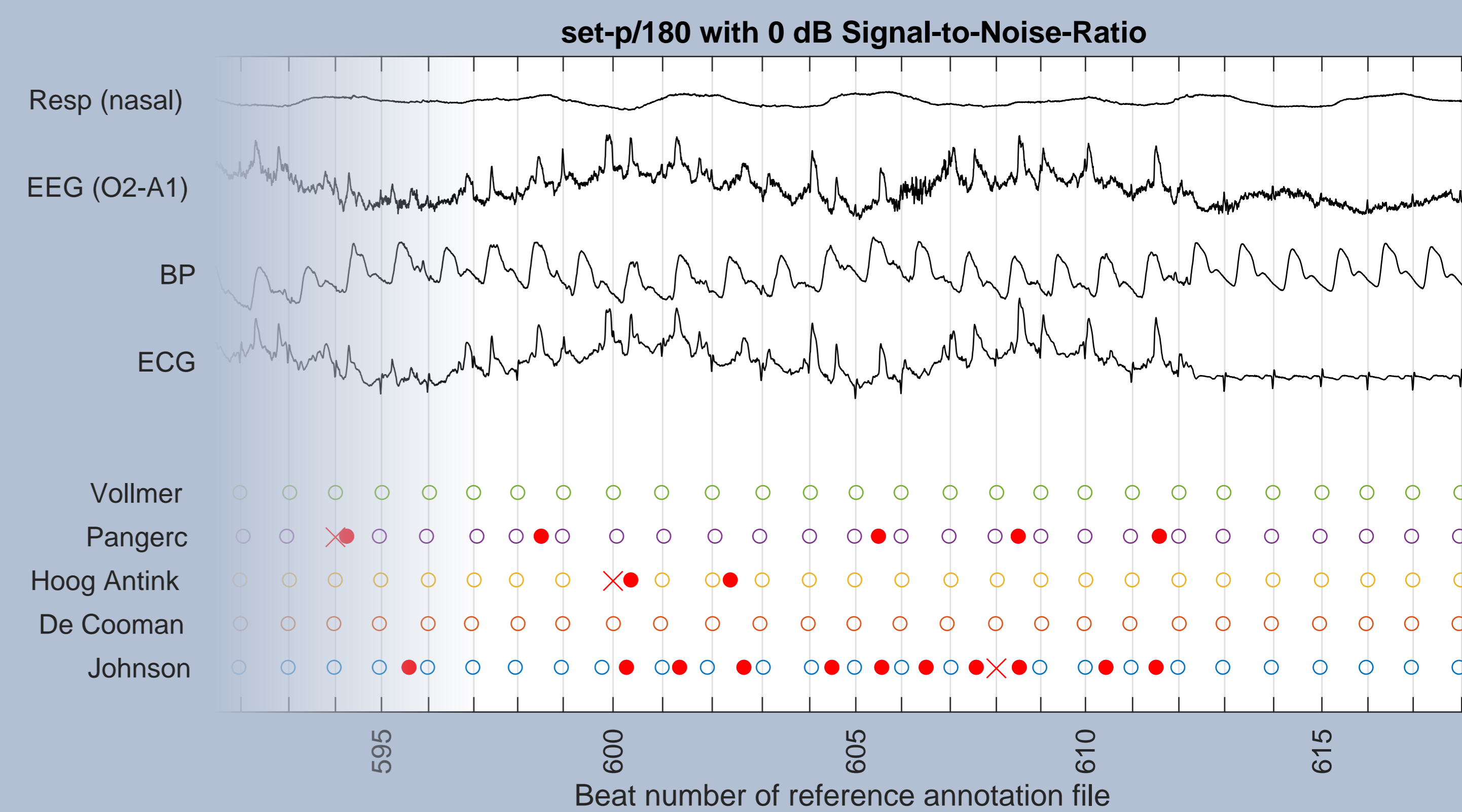
Implementation

Noisy records

- Transformed record set-p/180 with Signal-to-noise ratio (SNR) of 0 dB shows heavy weight of noise until beat number 612.
- Clean ECG signal on the right with the noisy segment on the left hand side. The baseline wander and many artifacts are visible.
- Although the blood pressure signal (BP) made a perfect annotation possible, only de Cooman and Vollmer are giving a correct annotation file in this particular example.

Noise Stress Test

Transition area of noisy and clean parts of a record. The noisy segment ends in the seventh minute with beat number 612. The ticks are set according to the reference annotation file. The added noise causes a large number of false positive (red dots) and false negative annotations (red crosses).



Structure of Evaluation

- Applying algorithms on modified set-p records with SNR between 24 and -6 dB.
- Comparing annotation files by detectors with reference annotations from clean records (gold standard of 150 ms).
- Computation of gross sensitivity and gross positive predictivity on basis of false positive and false negative counts.

Results

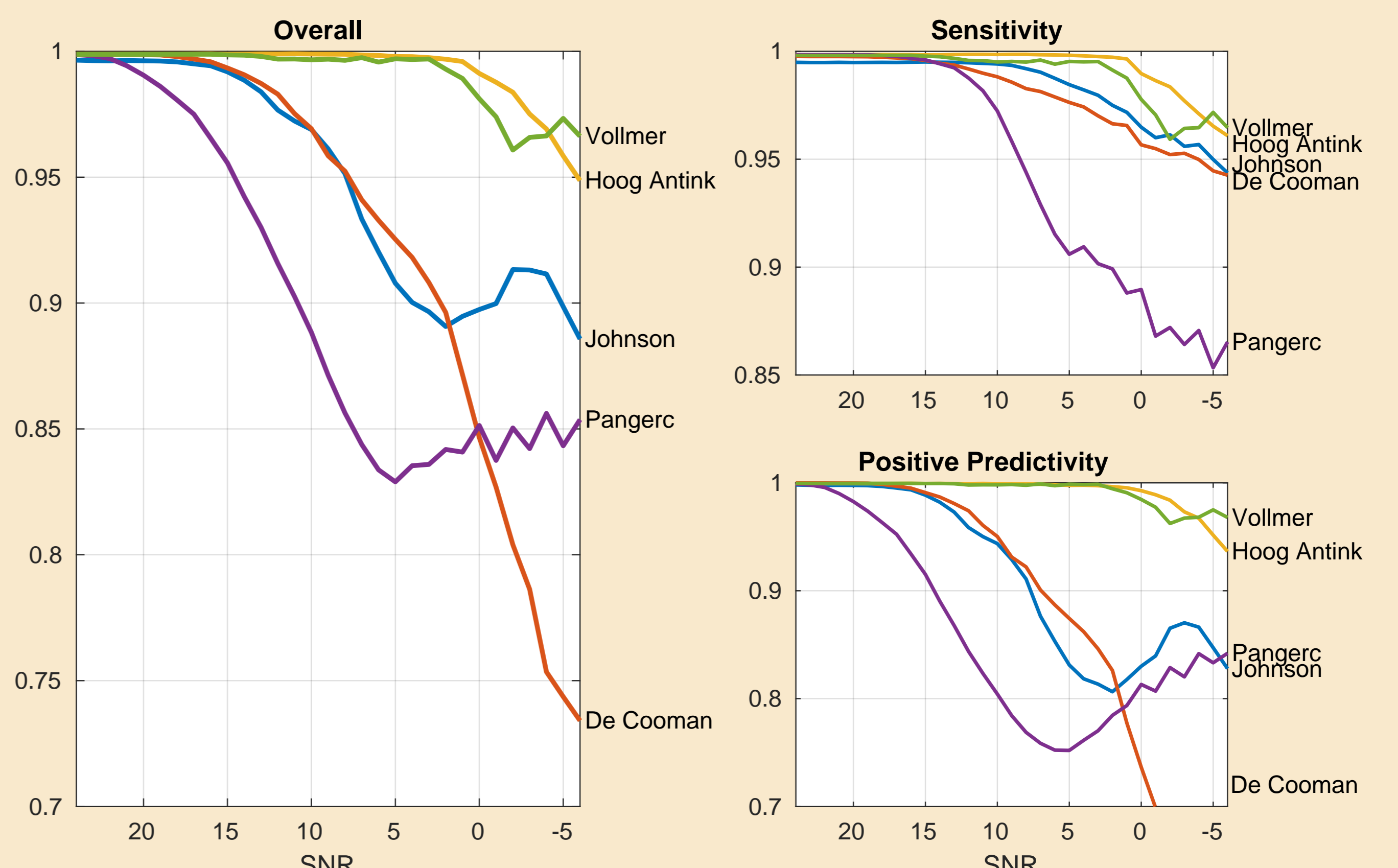
Course of noise resistance

- Pangerc' sensitivity is massively decreasing, starting already at 12 dB until SE=85 % has been reached at -6 dB. At the same time +P is decreasing as well, stops at 2 dB and increases interestingly until -3 dB. This is the effect of the "noise detection function" g_n , which rejects possible heart beats in noisy segments¹⁰.
- Johnson's +P has its minimum of 76% at 5 dB. Similarly to Pangerc, many artifacts (false-positives) has been annotated until a threshold has been reached. A higher SNR will result in the behavior that both algorithms will generally detect less heart beats, such that the +P is going to increase again at the costs of SE. As the result of the signal quality based fusion procedure (see 2.3.1 in²) which lowers the acceptance of heart beats when the estimated signal quality drops down.
- Remarkable noise resistant are the annotations of **Hoog Antink und Vollmer**. The **SE and +P statistics sticks at almost 100 % even until 0 dB**.
- Vollmer⁶ has used some signal quality index based on the regularity of RR interval series and an annotation threshold based on the difference between a smoothed windowed maximum and smoothed windowed minimum. The effect as seen in Figure aside results in both, SE and +P tends to remain static as of -2 dB.

Noise Resistance

Noise resistance of several heart beat detectors participated in the PhysioNet/CinC Challenge 2014 evaluated on noisy set-p records at different signal-to-noise ratios. Left: overall score. Right: average sensitivity and positive predictivity within the noisy segments.

10 dB corresponds to 10-fold stronger signal than noise (10:1).
3 dB \equiv 2:1, -6 dB \equiv 1:4.



[1] U. Pangerc and F. Jager, "Robust detection of heart beats in multimodal records using slope- and peak-sensitive band-pass filters," *Physiological Measurement*, vol. 36, no. 8, p. 1645, 2015.
[2] A. E. W. Johnson, J. Behar, F. Androotti, G. D. Clifford, and J. Oster, "Multimodal heart beat detection using signal quality indices," *Physiological Measurement*, vol. 36, no. 8, p. 1665, 2015.
[3] C. Hoog Antink, C. Brüser, and S. Leonhardt, "Detection of heart beats in multimodal data: a robust beat-to-beat interval estimation approach," *Physiological Measurement*, vol. 36, no. 8, p. 1679, 2015.
[4] T. de Cooman, G. Goovaerts, C. Varon, D. Widjaja, T. Willemen, and S. van Huffel, "Heart beat detection in multimodal data using automatic relevant signal detection," *Physiological Measurement*, vol. 36, no. 8, p. 1691, 2015.
[5] L. Galeotti, C. G. Scully, J. Vicente, L. Johannessen, and D. G. Strauss, "Robust algorithm to locate heart beats from multiple physiological waveforms by individual signal detector voting," *Physiological Measurement*, vol. 36, no. 8, p. 1705, 2015.
[6] M. Vollmer, "Robust Detection of Heart Beats using Dynamic Thresholds and Moving Windows," in *Computing in Cardiology*, pp. 569-572, 2014.
[7] I. Silva, B. Moody, J. Behar, A. Johnson, J. Oster, G. D. Clifford, and G. B. Moody, "Robust detection of heart beats in multimodal data," *Physiological Measurement*, vol. 36, no. 8, p. 1629, 2015.
[8] G. B. Moody, W. Muldrow, and R. G. Mark, "A noise stress test for arrhythmia detectors," *Computers in Cardiology*, vol. 11, no. 3, pp. 381-384, 1984.
[9] G. B. Moody, *WFDB applications guide*. Harvard-MIT Division of Health Sciences and Technology, 10 ed., 2003.
[10] U. Pangerc and F. Jager, "Robust detection of heart beats in multimodal data using integer multiplier digital filters and morphological algorithms," in *Computing in Cardiology*, pp. 285-288, 2014.



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Supported by the DZHK (German Centre for Cardiovascular Research).



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