Comparison of Statistical Model-Based Voice Activity Detectors for Mobile Robot Speech Applications

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Motivation

- A necessary front-end for robotic speech applications

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- Speaker localization, speaker identification or speech recognition
- Focus on statistical model-based voice activity detectors

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$$H_1 : \text{speech present} \Rightarrow \mathbf{X} = \mathbf{N} + \mathbf{S},$$

where $\mathbf{X}$, $\mathbf{N}$ and $\mathbf{S}$ are the DFT coefficients of a K-point DFT of the noisy speech, noise, and clean speech

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$$\Lambda_k = \frac{p(X_k|H_1)}{p(X_k|H_0)}$$

- Geometric mean

$$\log \Lambda = \frac{1}{K} \sum_{k=0}^{K-1} \log \Lambda_k \underset{H_0}{\overset{H_1}{\gtrless}} \eta$$

Gaussian distribution [Sohn et al., 1999]

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- Joint distribution

$$\begin{aligned} p(S_k) = p(S_{R,k})p(S_{I,k}) &= \frac{1}{\pi\lambda_{s,k}} \exp\left(-\frac{S_{R,k}^2 + S_{I,k}^2}{\lambda_{s,k}}\right) \\ &= \frac{1}{\pi\lambda_{s,k}} \exp\left(-\frac{|S_k|^2}{\lambda_{s,k}}\right) \end{aligned} \tag{1}$$

Gaussian distribution [Sohn et al., 1999]

- Two hypotheses

$$p(X_k|H_0) = \frac{1}{\pi\lambda_{n,k}} \exp\left\{-\frac{|X_k|^2}{\lambda_{n,k}}\right\}$$

$$p(X_k|H_1) = \frac{1}{\pi(\lambda_{n,k} + \lambda_{s,k})} \cdot \exp\left\{-\frac{|X_k|^2}{\lambda_{n,k} + \lambda_{s,k}}\right\}$$

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- Likelihood ratio for GD VAD

$$\Lambda_k^{\mathrm{GD}} = \frac{p(X_k|H_1)}{p(X_k|H_0)} = \frac{1}{1+\xi_k} \exp\left\{\frac{\gamma_k \xi_k}{1+\xi_k}\right\},$$

where $\xi_k = \lambda_{s,k}/\lambda_{n,k}$ is the *a priori* SNR, and $\gamma_k = |X_k|^2/\lambda_{n,k}$ is the *a posteriori* SNR

Generalized Gaussian distribution [Chang et al., 2004]

- Joint distribution

$$p(S_k) = \frac{\nu^2 \alpha^2(\nu)}{4\lambda_{s,k}\Gamma^2(1/\nu)} \cdot \exp\left\{-\alpha^\nu(\nu)\left[\left|\frac{S_{R,k}}{\sqrt{\lambda_{s,k}}}\right|^\nu + \left|\frac{S_{I,k}}{\sqrt{\lambda_{s,k}}}\right|^\nu\right]\right\}$$

with

$$\alpha(\nu) = \sqrt{\frac{\Gamma(3/\nu)}{\Gamma(1/\nu)}}$$

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- Likelihood ration for GGD VAD

$$\begin{aligned} \Lambda_k^{GGD} =& \frac{1}{1+\xi_k} \cdot \frac{\nu_{s,k}^2 \alpha^2(\nu_{s,k}) \Gamma^2(1/\nu_{n,k})}{\nu_{n,k}^2 \alpha^2(\nu_{n,k}) \Gamma^2(1/\nu_{s,k})} \exp \Bigg\{ \\ & - \alpha^{\nu_{s,k}}(\nu_{s,k}) \left[\frac{|X_{R,k}|^{\nu_{s,k}} + |X_{I,k}|^{\nu_{s,k}}}{\left(\sqrt{\lambda_{n,k}(1+\xi_k)}\right)^{\nu_{s,k}}} \right] + \\ & + \alpha^{\nu_{n,k}}(\nu_{n,k}) \left[\frac{|X_{R,k}|^{\nu_{n,k}} + |X_{I,k}|^{\nu_{n,k}}}{\left(\sqrt{\lambda_{n,k}}\right)^{\nu_{n,k}}} \right] \Bigg\} \end{aligned} \tag{2}$$

Rayleigh-Rice distribution [Mumolo et al., 2003]

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- Under hypothesis H_1 we have Rice distribution

$$p(X_k|H_1) = \frac{2|X_k|}{\lambda_{n,k}} \exp\left\{-\frac{|X_k|^2}{\lambda_{n,k}} - \xi_k\right\} \cdot I_0\left\{2\sqrt{\xi_k \frac{|X_k|^2}{\lambda_{n,k}}}\right\}$$

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- Likelihood ratio for RRD VAD

$$\Lambda_k^{\mathrm{RRD}} = \exp\{-\xi_k\}\, I_0\left\{2\sqrt{\xi_k \gamma_k}\right\}$$

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$$\lambda_{n,k}(l) = \alpha\lambda_{n,k}(l-1) + (1-\alpha)|X_k(l)|^2$$

- ζ_k is calculated via decision directed a-priori SNR estimation [Ephraim and Malah, 1984]

$$\xi_k(l) = f(\xi_k(l-1), \gamma_k(l-1), \gamma_k(l))$$

- NOIZEUS [Hu and Loizou, 2007] speech corpus (sound-proof booth, various noise added at different SNR levels, ...)

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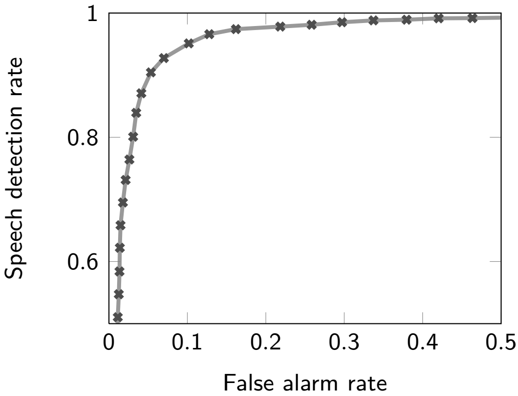
- We used car, babble, and white noise at three different SNR levels (15, 10, 5 dB)
- With 50% overlap we had 50000 examples, out of which 61.28% contained speech

Receiver operating characteristics

- depict relationship between speech detection rate and false alarm rate



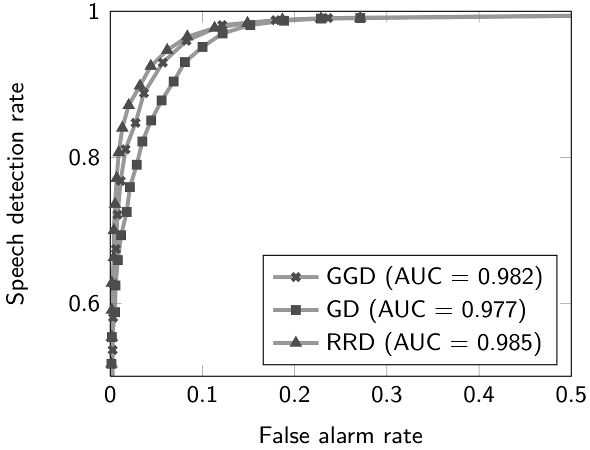


Figure: Clean speech signal

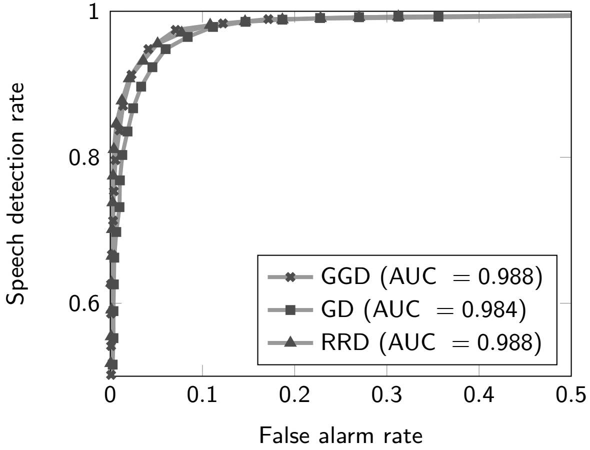


Figure: Speech corrupted with white Gaussian noise at SNR 15 dB

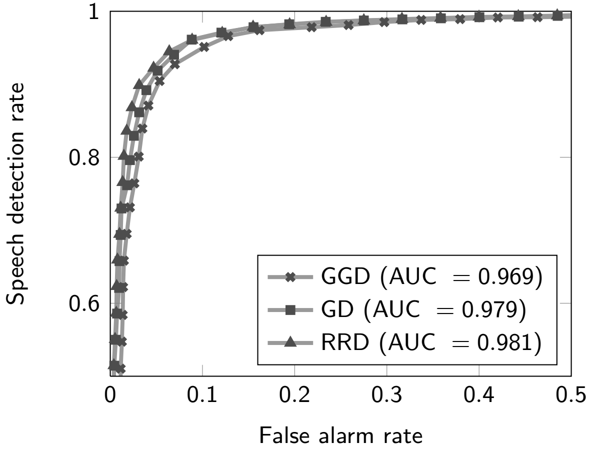


Figure: Speech corrupted with car noise at 10 dB

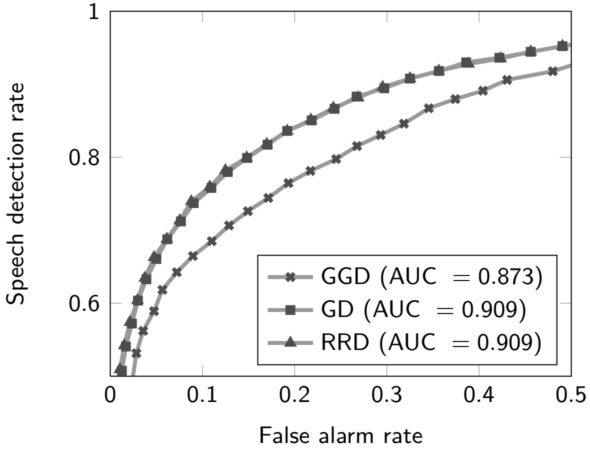


Figure: Speech corrupted with babble noise at 5 dB

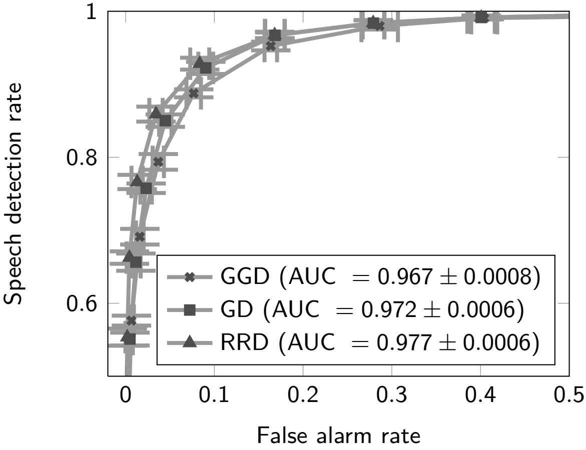


Figure: Threshold averaged ROC curves with area under curve scores

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- Execution time: GGD 9.70 ms, RRD 0.37 ms, GD 0.21 ms

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- Decision based on geometric mean of a likelihood ratio
- Experimental analysis on NOIZEUS speech corpus
- Evaluation done with ROC curves and the AUC score
- RRD based VAD is the method of choice

Future work

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- Utilize machine learning algorithms for decision making (SVM, Neural networks, Boost)
- Perform input variable analysis

Thank you for your attention

Questions?

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