

Microphone Array For Headset With Spatial Noise Suppressor

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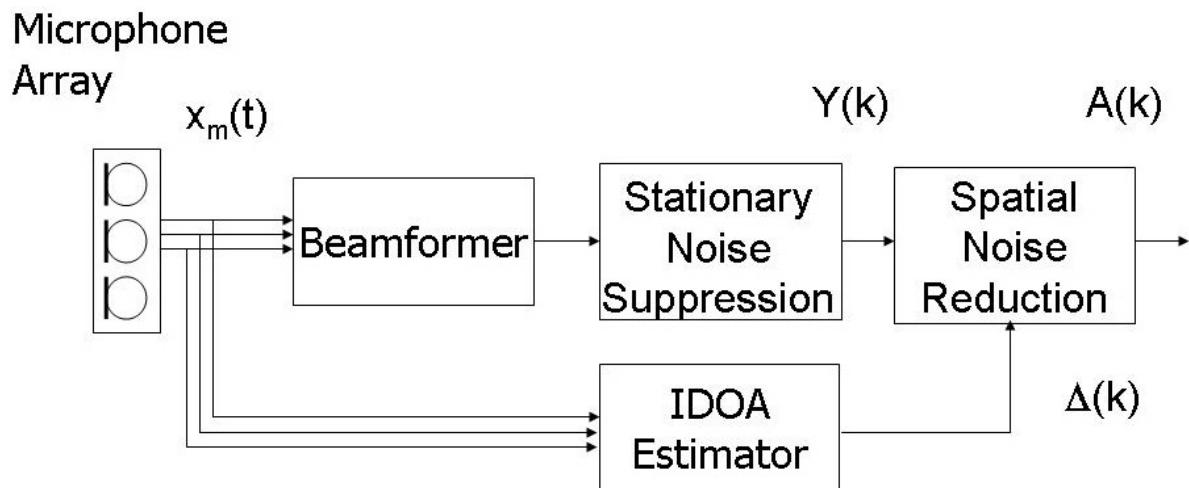
Problem and solutions

- Problem: Providing good quality sound capture with a small headset
 - A short boom loses 6 dB in SNR
- Solution: Using multiple microphones for beamforming and spatial filtering
- Constraints: Low CPU usage, memory footprint and price, long battery life



Solution architecture

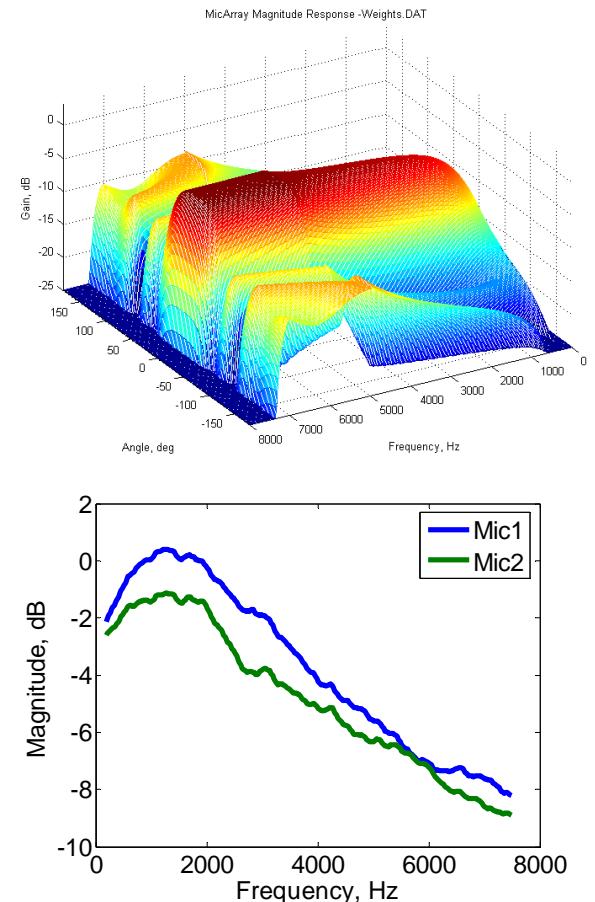
- 3 element microphone array
- Time invariant beamformer
- Stationary noise suppressor
- Spatial noise suppressor

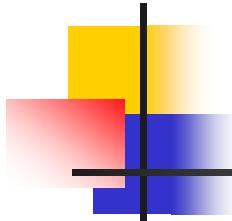


Time-Invariant Beamformer

- Processing in frequency domain
- Weights computed using deterministic algorithm
- Trade-off: better directivity for more instrumental noise
- Compensation for the diffraction around the head

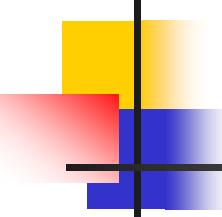
$$Y(f) = \sum_{m=1}^M W_m(f) X_m(f)$$





Stationary Noise Suppressor

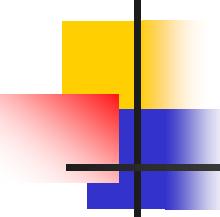
- High time constant for building the noise model
- Probabilistic Gaussian classifier for VAD
 - Variants: using a bone microphone or an accelerometer for robust detection
- Suppression rule based on MMSE Spectral Power Estimator (P. Wolfe and S. Godsil, 2003) – efficient version of Ephraim and Malah suppression rule (1984)



Noise suppression

- Signal $x_n(t)$ and noise $d_n(t)$ mixed in $y_n(t)$
- Observed: $Y_k = X_k + D_k$
- Noise suppression: $\hat{X}_k = H_k \cdot Y_k$
- H_k – suppression rule, real vector.
Keep the same phase as Y_k
- Signal variances $\lambda_X(k), \lambda_D(k), \lambda_Y(k)$
- *a priori* and *a posteriori* SNRs

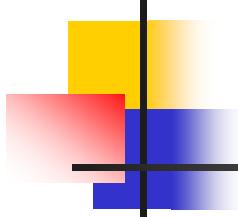
$$\xi(k) \triangleq \frac{\lambda_X(k)}{\lambda_D(k)}, \gamma(k) \triangleq \frac{|Y(k)|^2}{\lambda_D(k)}, v(k) \triangleq \frac{\xi_k}{1 + \xi_k} \gamma_k$$



Common Suppression Rules

- Weiner suppression rule (1945): $H(k) = \frac{\lambda_x(k)}{\lambda_x(k) + \lambda_D(k)}$
- Ephraim and Malah rule (1984):
$$H_k = \frac{\sqrt{\pi\nu_k}}{2\gamma_k} \left[(1+\nu_k) I_0\left(\frac{\nu_k}{2}\right) + \nu_k I_1\left(\frac{\nu_k}{2}\right) \right] \exp\left(-\frac{\nu_k}{2}\right)$$
- Efficient alternatives, P. Wolfe & S. Godsil (2003):
 - Joint Maximum A Posteriori Spectral Amplitude Estimator
 - Maximum A Posteriori Spectral Amplitude Estimator
 - Minimum Mean Square Error Spectral Power Estimator

$$H_k = \sqrt{\frac{\xi_k}{1+\xi_k} \left(\frac{1+\nu_k}{\gamma_k} \right)}$$



Variation and SNR estimations

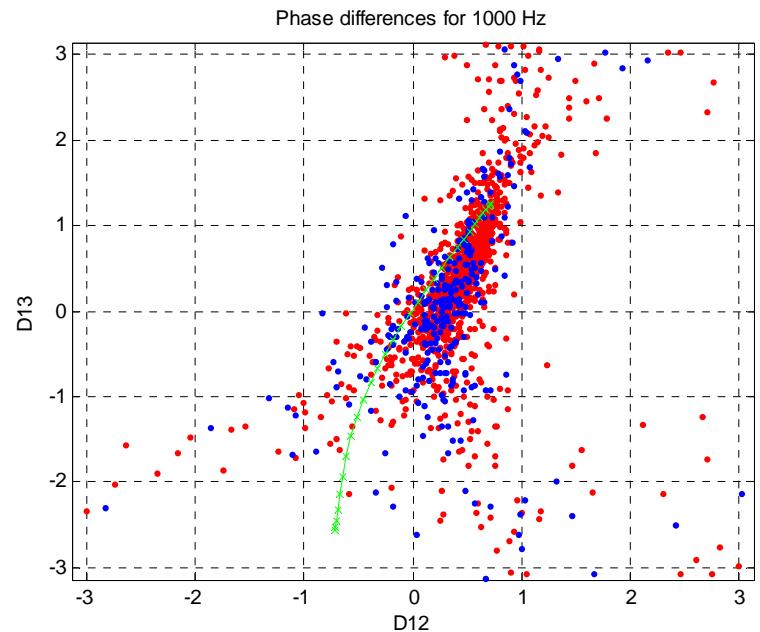
- Noise variation estimation
 - Use VAD to classify the audio frames
 - For non-voiced frames update the noise model: $\lambda_D(n,k) = (1 - \beta)\lambda_D(n-1,k) + \beta|Y(n,k)|^2$
- *a priori* SNR estimation:
 - Approximate: $\hat{\xi}(k) = \frac{|Y(k)|^2 - \lambda_D(k)}{\lambda_D(k)}$
 - Decision-directed (Ephraim and Malah):
$$\hat{\xi}(k) = \alpha \frac{|\hat{X}(n-1,k)|^2}{\lambda_D(n-1,k)} + (1 - \alpha) \max[0, \gamma(n,k) - 1], \alpha \in [0,1]$$

Spatial Noise Reduction

- With microphone array the signals have position, i.e. one more dimension
- Instant Direction Of Arrival (IDOA) space:

$$\Delta(f) \triangleq [\delta_1(f), \delta_2(f), \dots, \delta_{M-1}(f)]$$

where $\delta_{j-1}(f) = \arg(X_1(f)) - \arg(X_j(f))$



Estimation and suppression

- Signal and noise variances

$$\lambda_Y(f | \Delta) \triangleq E[|Y(f | \Delta)|^2]$$

$$\lambda_D(f | \Delta) \triangleq E[|D(f | \Delta)|^2]$$

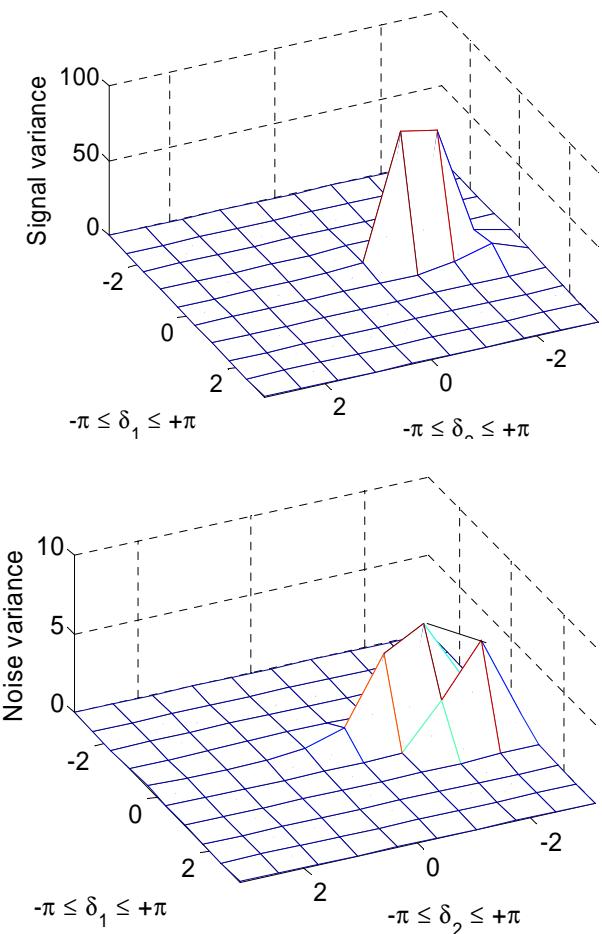
- *a priori* and *a posteriori* SNR

$$\xi(f | \Delta) \triangleq \beta \frac{\lambda_Y(f | \Delta) - \lambda_D(f | \Delta)}{\lambda_D(f | \Delta)} + (1 - \beta) \max[0, \gamma(f | \Delta)], \beta \in [0, 1)$$

$$\gamma(f | \Delta) \triangleq \frac{|Y(f | \Delta)|^2}{\lambda_D(f | \Delta)}$$

- Suppression rule

$$H(f | \Delta) = \sqrt{\frac{\xi(f | \Delta)}{1 + \xi(f | \Delta)} \left(\frac{1 + \vartheta(f | \Delta)}{\gamma(f | \Delta)} \right)}$$



Results

■ SNR improvement

	<i>BM</i>	<i>BF</i>	<i>NS</i>	<i>SR</i>
Office, 55 dB	25.2	22.5	29.4	34.7
Café, 75 dB	7.2	12.3	17.5	22.8
Car, 90 dB	3.2	6.4	11.1	16.4

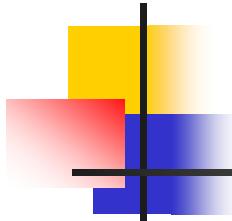
BM – best microphone,

BF – beamformer

NS – noise suppressor

SR – spatial noise suppressor





How it sounds?

- 75 dB cocktail party noise

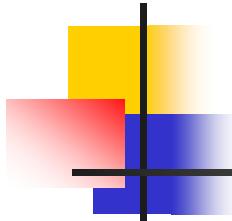


Input Output

- 90 dB in-car noise

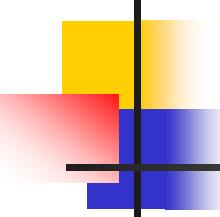


Input Output



Conclusions

- Presented processing algorithm provides noise reduction up to 14 dB
- It uses a priori known properties of the estimated signal and suppressed noise:
 - Stationary noise
 - Short-term-stationary signal
 - Spatially-stationary noise and signal
- Well balanced suppression from each stage provides low level distortions and artifacts
- Low scalability due to dimensions increasing



Finally

The art of noise suppression and reduction is knowing when to stop.

Thank you for your attention!

Questions?