

# **Detecting Acoustic Reflectors using a Robot's Ego-Noise**

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### **1. Introduction**

- Ego-noise is considered as a source of problem in many robotic applications, as it corrupts audio recordings captured by microphones [Nakadai, 2000][Okuno, 2015]
- Ego-noise reduction is an active area of research that plays an important role in many autonomous systems [Wake, 2019], and has enabled applications such as speech recognition for HRI or acoustic scene analysis
- Instead of treating ego-noise as a source of problem, we propose utilizing ego-noise constructively for acoustic reflector, e.g., wall, localization
- ► We propose an estimator for acoustic reflectors based on the *time dif*-

3. Ego-noise-based acoustic reflector estimation and detection

$$\{\Delta \widehat{\tau}, \widehat{\alpha}\} = \underset{\Delta \tau, \alpha}{\operatorname{arg\,min}} \|\mathbf{y} - (\mathbf{I} + \alpha \mathbf{D}_{\Delta \tau}) \mathbf{x}_d\|^2$$
$$= \underset{\Delta \tau, \alpha}{\operatorname{arg\,min}} J(\Delta \tau, \alpha).$$

By zeroing the derivative with respect to  $\alpha$  we get:

$$\frac{\delta J}{\delta \alpha} = -\mathbf{y}^T \mathbf{D}_{\Delta \tau} \mathbf{x}_d - \mathbf{x}_d^T \mathbf{D}_{\Delta \tau}^T \mathbf{y} + \mathbf{x}_d^T \mathbf{D}_{\Delta \tau}^T \mathbf{x}_d + \mathbf{x}_d^T \mathbf{D}_{\Delta \tau} \mathbf{x}_d + 2\alpha \mathbf{x}_d^T \mathbf{D}_{\Delta \tau}^T \mathbf{D}_{\Delta \tau} \mathbf{x}_d = 0.$$

ference of echo (TDOE) which exploits the comb-filtering effect that emerges from the direct-path component of the sound source mixing with its delayed version, due to the presence of the acoustic reflector

#### 2. Problem Statement

Consider a setup with a single microphone that records both the egonoise generated by the rotors of a drone, x[n], and a background noise from the environment v[n]. The signal model is then:

> y[n] = (h \* s)[n] + v[n] = x[n] + v[n],(1)

Furthermore, we can rewrite (1) in a compact expression by separating x[n] into the direct-path and early reflection components as:

> $y[n] = x_d[n] + x_r[n] + v'[n],$ (2)

where  $x_d[n] = g_1 s[n - \tau_1]$  and  $x_r[n] = \sum_{q=2}^R g_q s[n - \tau_q]$  contains all the early reflections. If we vectorize (2) and express it in terms of the gains and delays:

> $\mathbf{y}[n] \approx g_d \mathbf{D}_{\tau_d} \mathbf{s}[n] + g_r \mathbf{D}_{\tau_r} \mathbf{s}[n] + \mathbf{v}'[n],$ (3)

By observing that  $\mathbf{D}_{\Delta\tau}^{T}\mathbf{D}_{\Delta\tau} = \mathbf{I}$ , this becomes:

$$\widehat{\alpha}(\Delta \tau) = \frac{(\mathbf{y} - \mathbf{x}_d)^T \mathbf{D}_{\Delta \tau} \mathbf{x}_d}{\|\mathbf{x}_d\|^2}.$$

 $\Delta \widehat{\tau} = \arg \max \widehat{\alpha} (\Delta \tau)^2.$ 

Let us consider the following two hypotheses:

 $\mathcal{H}_0: \mathbf{y}[n] = \mathbf{x}_d[n] + \mathbf{v}[n],$  $\mathcal{H}_1: \mathbf{y}[n] = \mathbf{x}_r[n] + \mathbf{x}_d[n] + \mathbf{v}[n],$ 

(11)(12)

(6)

(7)

(8)

(9)

(10)

the generalized likelihood ratio test (GLRT) is given as:

$$\mathcal{L}(n) = \frac{p(\mathbf{y}; \mathbf{x}_r[n], \mathcal{H}_1)}{p(\mathbf{y}; \mathcal{H}_0)} > \gamma.$$
(13)

The probability density functions (PDFs) for the two hypotheses are given as shown:

 $\mathcal{N}(\mathbf{x}_d[n] + \mathbf{v}[n], \sigma^2),$ 

 $\mathbf{y}[n] = \begin{bmatrix} y[n] & y[n+1] & \cdots & y[n+N-1] \end{bmatrix}^T,$ 

where  $\mathbf{D}_{\tau}$  is a cyclic shift register. Assuming R = 2, the signal  $\mathbf{x}_r[n]$  is then a delayed version of the direct-path component, (3) can be expressed as shown:

$$\mathbf{y}[n] = \mathbf{x}_{d}[n] + \frac{g_{r}}{g_{d}} \mathbf{D}_{\Delta \tau} \mathbf{x}_{d}[n] + \mathbf{v}'[n], \qquad (4)$$
$$= (\mathbf{I} + \alpha \mathbf{D}_{\Delta \tau}) \mathbf{x}_{d}[n] + \mathbf{v}'[n], \qquad (5)$$

where  $\Delta \tau$  is the TDOE of the observed signal, such that  $\Delta \tau = \tau_r - \tau_d$  and  $\alpha = \frac{g_r}{a_d}$ , while I is the identity matrix.

 $\mathcal{N}(\mathbf{x}_r[n] + \mathbf{x}_d[n] + \mathbf{v}[n], \sigma^2),$ 

(15)

(14)

where  $\sigma_v^2$  is the variance of the background noise, v[n].

$$\ln \mathcal{L}(\mathbf{x}) = \ln \frac{p(\mathbf{y}; \mathbf{x}_r[n], \mathcal{H}_1)}{p(\mathbf{y}; \mathcal{H}_0)} = (\mathbf{y}[n] - \mathbf{x}_d[n])^T (\mathbf{y}[n] - \mathbf{x}_d[n]) > 2\sigma_v^2 \ln \gamma.$$
(16)

Hence, the criterion to detect an acoustic reflector is:

$$T(\mathbf{y}) = \|\mathbf{y}[n] - \mathbf{x}_d[n]\|^2 \underset{H_0}{\overset{H_1}{\geq}} 2\sigma_v^2 \ln \gamma.$$

## 4. Experiments



![](_page_0_Figure_45.jpeg)

![](_page_0_Figure_46.jpeg)

#### 5. Conclusion

- In this paper, we proposed a TDOE estimator and an echo detector to estimate the proximity of an acoustic reflector.
- The proposed method could lead to the development of new sound-based collision avoidance systems for, e.g., drones.
- The proposed method is robust against active/intrusive approach proposed by [Saqib, 2019] as shown in Fig. 1.
- The proposed method detects an acoustic reflector up to a distance of 1 m under low SDNRs as shown in Fig. 2