

# Optimal Sensor Fusion using $\mathcal{H}_{\infty}$ methods

## Terrence T.L. Tsang on behalf of the KAGRA Collaboration

The Chinese University of Hong Kong. Email: ttltsang@link.cuhk.edu.hk



#### Introduction: Complementary Filters at KAGRA

- ► The pre-isolators of Type-A and Type-B suspensions in KAGRA are equipped with relative sensors and inertial sensors.
- ► A pair of complementary filters (low-pass and high-pass) can be used to combine the sensors into a virtual "super-sensor" that has superior noise properties.
- In this work, we discuss a scheme that uses  $\mathcal{H}_{\infty}$  methods to synthesize complementary filters that optimally blend the sensors according to the sensor noises.

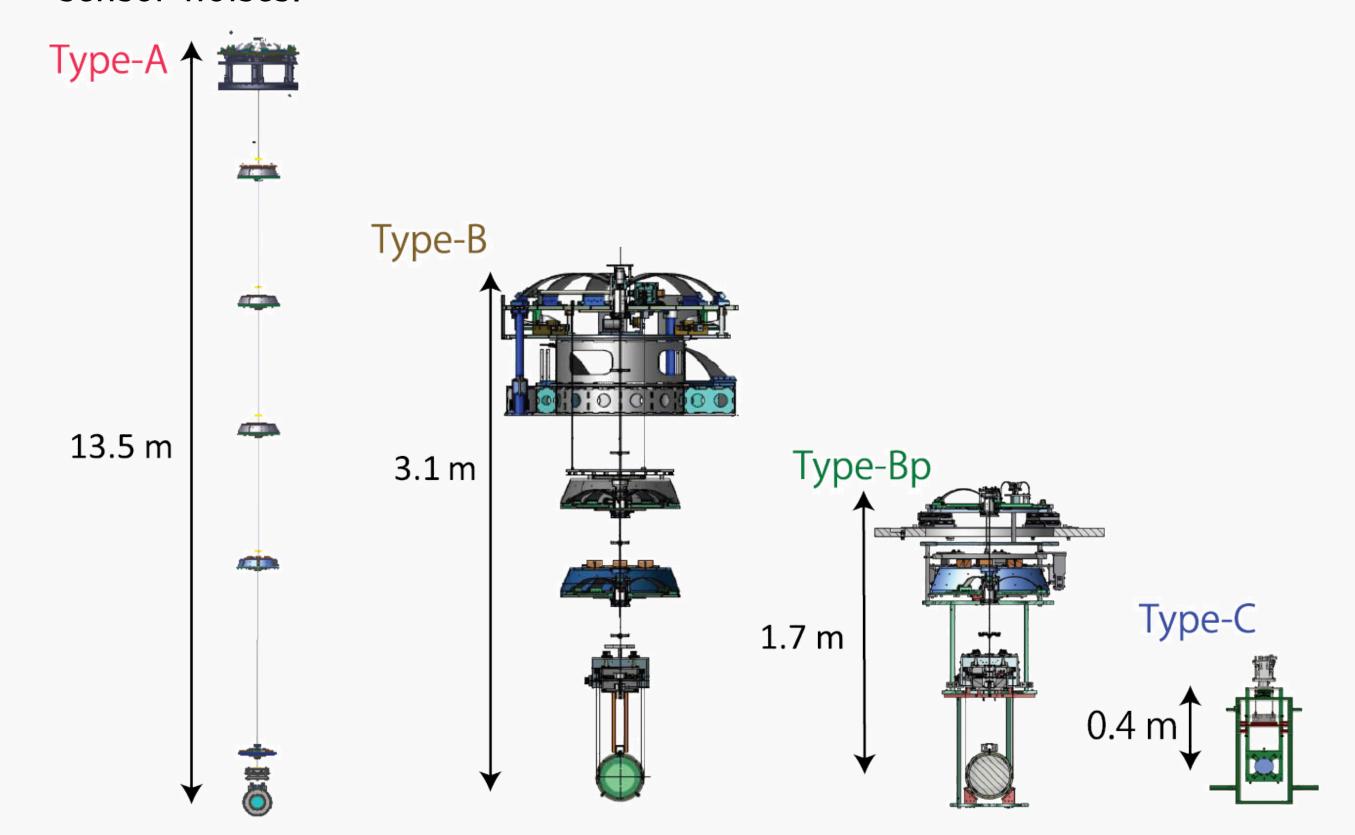


Figure 1: Type-A suspensions: input/end test masses, Type-B suspensions: beamsplitter and signal-recycling mirrors, Type-Bp suspensions: power-recycling mirrors, and Type-C suspensions: input/output mode cleaners [1].

### Methodology: Complementary Filter Problem as an $\mathcal{H}_{\infty}$ Problem

#### $\mathcal{H}_{\infty}$ method in a nutshell:

- 1. As shown in Fig. 2, define signals w, z, u, and v, and hence,
- 2. derive a generalized plant P(s).
- 3.  $\mathcal{H}_{\infty}$  synthesis gives an  $\mathcal{H}_{\infty}$ optimal controller  $\mathbf{K}_{\infty}(s)$  that minimizes the  $\mathcal{H}_{\infty}$ -norm of the closed-loop plant  $\|\mathbf{G}(s; \mathbf{K}, \mathbf{P})\|_{\infty}$ .

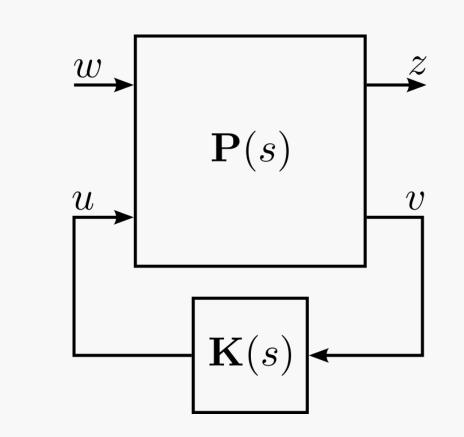


Figure 2: Generalized Plant Represenation.

▶ The close-loop transfer function  $\mathbf{G}(s)$  is defined such that  $z = \mathbf{G}(s)w$ and  $u = \mathbf{K}(s)v$ , i.e.

$$\mathbf{G}(s) = P_{11}(s) + P_{12}(s)\mathbf{K}(s)\left[\mathbf{I} - P_{22}(s)\mathbf{K}(s)\right]^{-1}P_{21}(s). \tag{1}$$

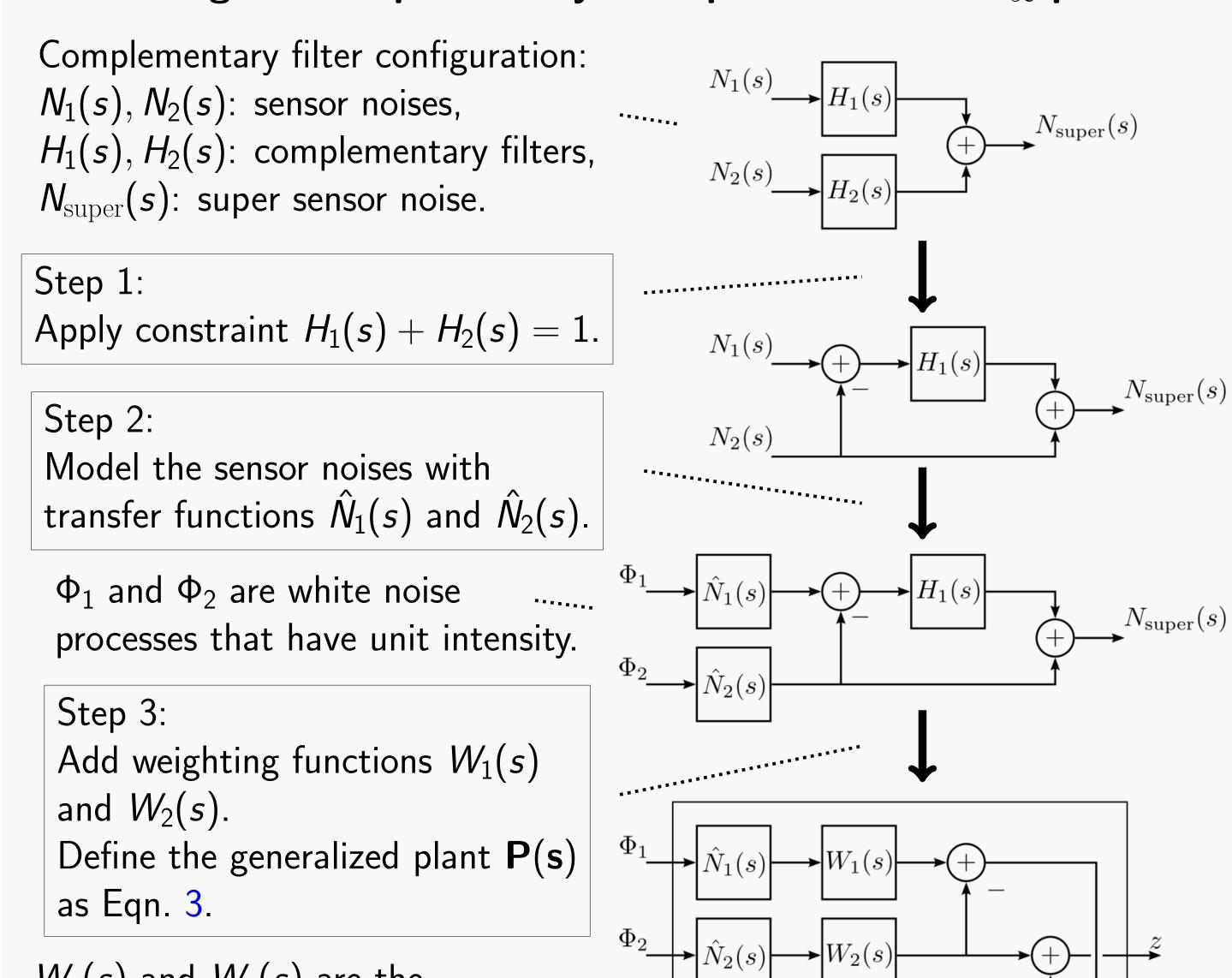
 $\blacktriangleright$  The  $\mathcal{H}_{\infty}$ -norm is defined as

$$\|\mathbf{G}(s)\|_{\infty} = \sup \bar{\sigma}(\mathbf{G}(j\omega)),$$
 (2)

where  $\bar{\sigma}$  denotes the maximum singular value and  $\omega$  is the angular trequency.

#### Methodology: Complementary Filter Problem as an $\mathcal{H}_{\infty}$ Problem Results: Complementary Filters for LVDTs and geophones

#### Formulating the complementary filter problem as an $\mathcal{H}_{\infty}$ problem:



 $W_1(s)$  and  $W_2(s)$  are the inverse of the frequency dependent specification of the sensor noises [2].

Finally:  $\mathcal{H}_{\infty}$  synthesis gives optimal  $H_1(s)$ , and get  $H_2(s)$  from  $1 - H_1(s)$ .

Figure 3: From a simple complementary filter configuration to generalized plant representation.

► The generalized plant is given by

$$\mathbf{P}(s) = \begin{bmatrix} 0 & \hat{N}_2(s)W_2(s) & 1 \\ \hat{N}_1(s)W_1(s) - \hat{N}_2(s)W_2(s) & 0 \end{bmatrix}. \tag{3}$$

► The closed-loop plant is given by

$$\mathbf{G}(s) = \left[ H_1(s) \hat{N}_1(s) W_1(s) H_2(s) \hat{N}_2(s) W_2(s) \right] . \tag{4}$$

- ▶ If we set  $W_1(s) = 1/\hat{N}_2(s)$  and  $W_2(s) = 1/\hat{N}_1(s)$ , then the target specification of  $N_1(s)$  is set to  $N_2(s)$  when  $|N_1(s)| \gg |N_2(s)|$ , and vice versa.
- ightharpoonup Minimizing  $\|\mathbf{G}(s)\|_{\infty}$  gives optimal complementary filters that minimizes the maximum difference between the super sensor noise and the lower bound of the sensor noise in logarithmic scale.
- ► This is equivalent to minimizing the cost function

$$J = \sup_{\omega} (\log |N_{\text{super}}(j\omega)| - \log \min(|N_1(j\omega)|, |N_2(j\omega)|)).$$
 (5)

- $ightharpoonup \mathcal{H}_{\infty}$  solvers are readily available in packages such as MATLAB and python-control.
- Complementary filters can be synthesized using the kontrol python package, which is developed for KAGRA's control systems.

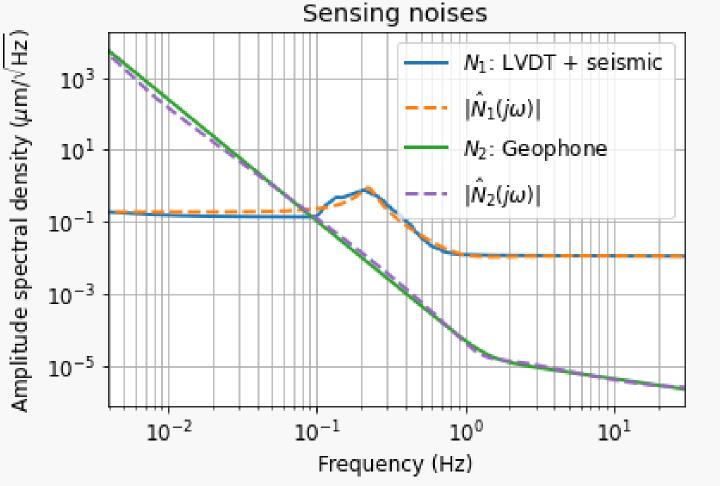


Figure 4: SRM sensor noises.

- Fig. 4: the empirical model of the seismic noise-coupled LVDT and geophone readout noises  $N_1$  and  $N_2$  and the transfer function models  $\hat{N}_1(s)$  and  $\hat{N}_2(s)$
- ► Fig. 5: The complementary filters synthesized using  $\mathcal{H}_{\infty}$  method.
- Fig. 6: The predicted super sensor noise using optimal complementary filters  $H_1(s)$  and  $H_2(s)$ .

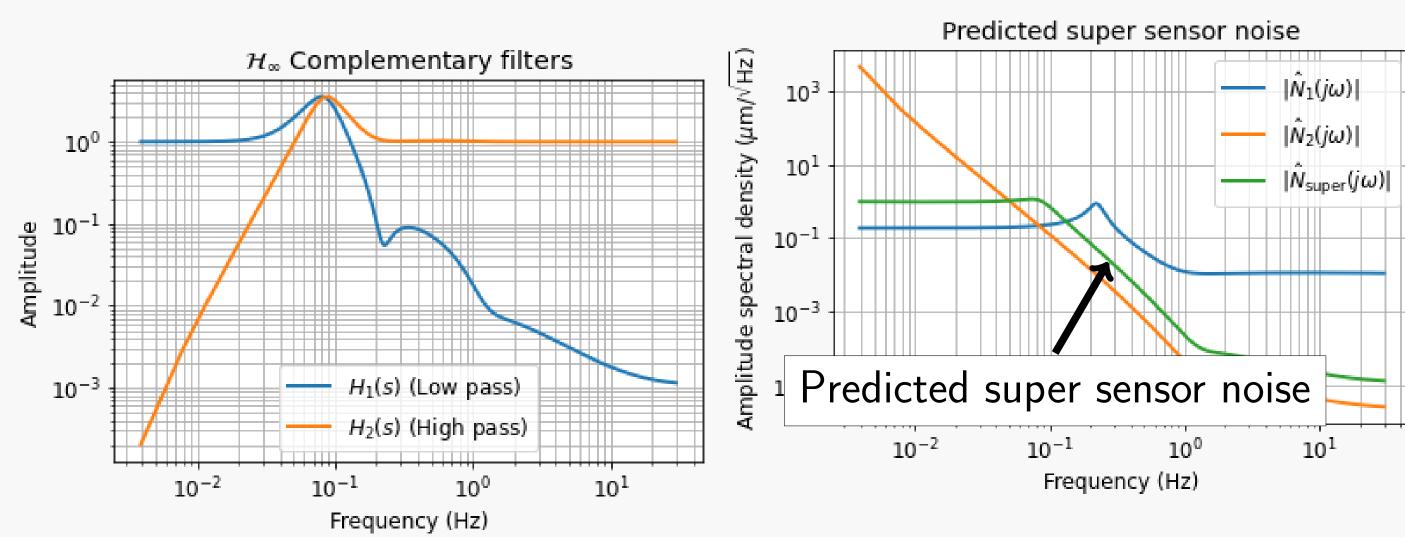


Figure 6: Predicted super sensor noise

Figure 5: Filters (using proposed method)

► The predicted super sensor noise is defined by

$$|\hat{N}_{\text{super}}(j\omega)| = \left[ |H_1(s)|^2 |\hat{N}_1(s)|^2 + |H_2(s)|^2 |\hat{N}_2(s)|^2 \right]^{\frac{1}{2}}.$$
 (6)

- ► The super sensor noise is equally close to the lower bound at all frequencies (logarithmically).
- ▶ Preliminary implementation results can be found in Ref. [3].

#### Discussion and Future work.

- ▶ Unlike static filter designs, such us those in Refs. [4, 5, 6], the proposed method can generate filters that is optimal for any arbitrary sensor noises.
- Sensor correction and feedback-control filters can both be formulated into a complementary filter configuration. They can both be solved using the same method.

#### References

- [1] T. Akutsu et al. Vibration isolation systems for the beam splitter and signal recycling mirrors of the KAGRA gravitational wave detector. Class. Quant. Grav., 38(6):065011, 2021.
- [2] Thomas Dehaeze, Verma Mohit, and Christophe Collette. Complementary filters shaping using  $\mathcal{H}_{\infty}$  synthesis. pages 459–464, 11
- [3] Terrence Tsang. SRM IP Longitudinal complementary filters synthesis using H-infinity method. https://klog.icrr.u-tokyo.ac.jp/osl/?r=17351
- [4] T. Sekiguchi. Study of Low Frequency Vibration Isolation System for Large Scale Gravitational Wave Detectors. PhD thesis, Tokyo U., 2016.
- [5] Joris Vincent van Heijningen. Turn up the bass! Low-frequency performance improvement of seismic attenuation systems and vibration sensors for next generation gravitational wave detectors. PhD thesis, Vrije U., Amsterdam, 2018.
- [6] Lucia Trozzo. Low Frequency Optimization and Performance of Advanced Virgo Seismic Isolation System. PhD thesis, Università degli Studi di Siena, 2018.