

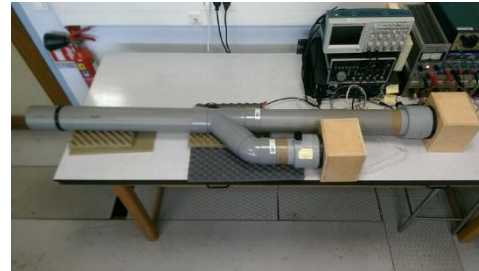
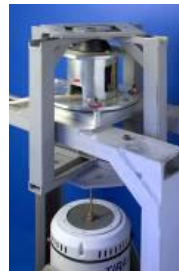
Adaptive Youla-Kucera Parametrization for Active Noise and Vibration Attenuation

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In collaboration with :

T. Airimitoiaie, R. Melendez, G. Buche and L. Dugard



ICSTCC, Sinaia, October 8-10 , 2020

Attenuation of vibrations and noise has become a major objective!

Why?

- Technological reasons
 - Environmental constraints
-
- Planes
 - Spatial platforms
 - Cars, trucks
 - Pipes
-
- Ships
 - Buildings
 - Manufacturing devices
 - Memory devices
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Techniques for noise and vibration attenuation:

- Passive** – use of materials having absorption properties
- Semi-active** – changing the properties of the absorbing materials and devices
- Active** – **use of an auxiliary source for compensating vibrations and noise**
- Adaptive** – **to take into account in real time the unknown and time varying characteristics of vibrations and noise.**

This presentation is concerned by « *adaptive active noise and vibration attenuation* »

Active noise and vibration attenuation – A control perspective

- Presence of resonant modes in physical structures can be a source of generation/amplification of noise and vibrations
- Active damping (active absorbers) is a basic control problem where by feedback one tries to damp the low damped modes taking into account the Bode Integral limitations (frequency shaping of the sensitivity function)
- Active damping may be adaptive in order to take into account large variabilities of the plant parameters.

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This is not the subject of this presentation!

Active noise and vibration attenuation – A control perspective

ANC – Active Noise Control

AVC – Active Vibration Control

- The challenging problem is to attenuate the effect of the propagation of vibrations and noise
- Noise or vibration are disturbances which have to be attenuated
- Passive and semi-active approaches do not allow to achieve enough attenuation and an active approach has to be used
- ANC and AVC require the introduction of a secondary source (an **actuator** in control terms)

Active noise and vibration attenuation – A control perspective

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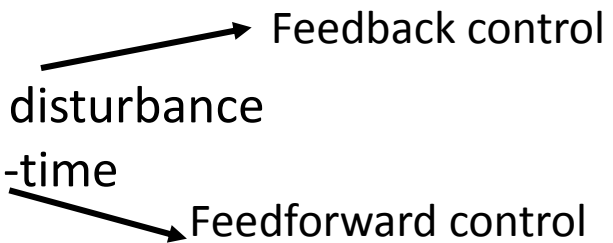
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Objective : Strong attenuation of the disturbance (noise or vibration)

*From a control point of view we have to solve a « **regulation** » problem*

ANC and AVC raise the same control problems (and of course use the same solutions)

Basic configurations for active noise and vibration attenuation

1. No information available in real time upon the disturbance
 2. An image of the disturbance is available in real-time
- Feedback control
- Feedforward control
- 

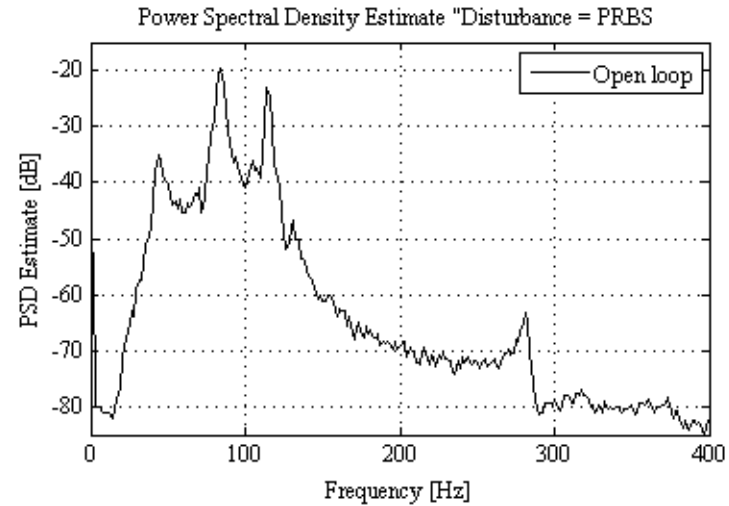
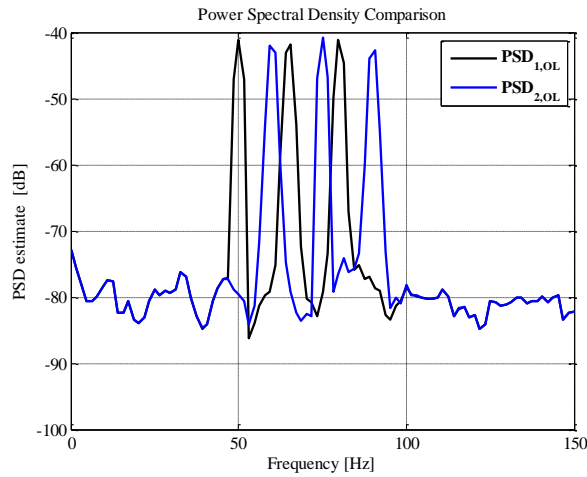
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Feedback control

Feedforward control

Narrow band disturbances



Broad band disturbances

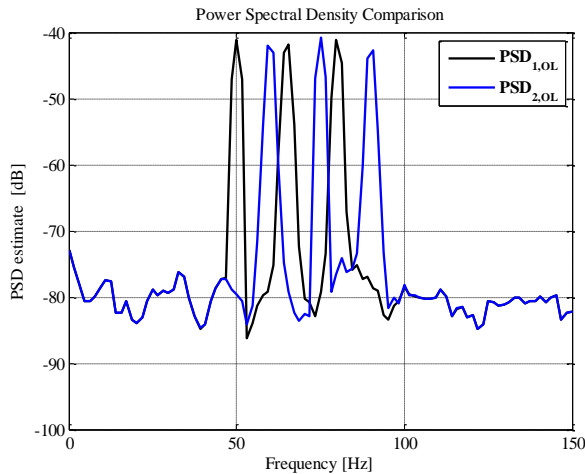
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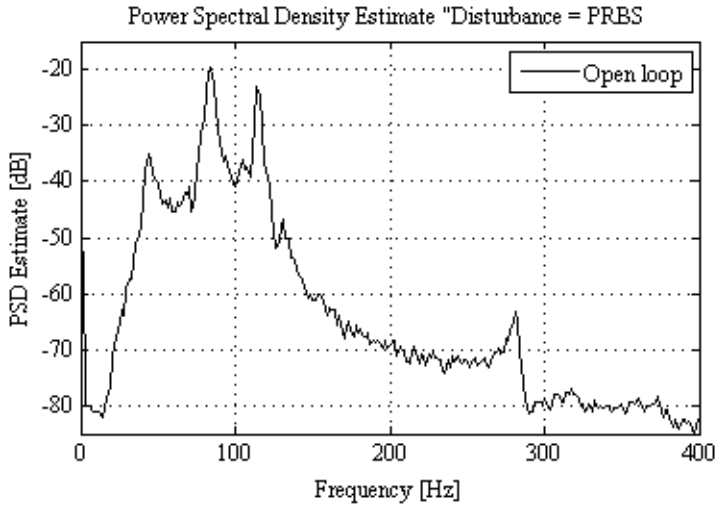
Feedback control

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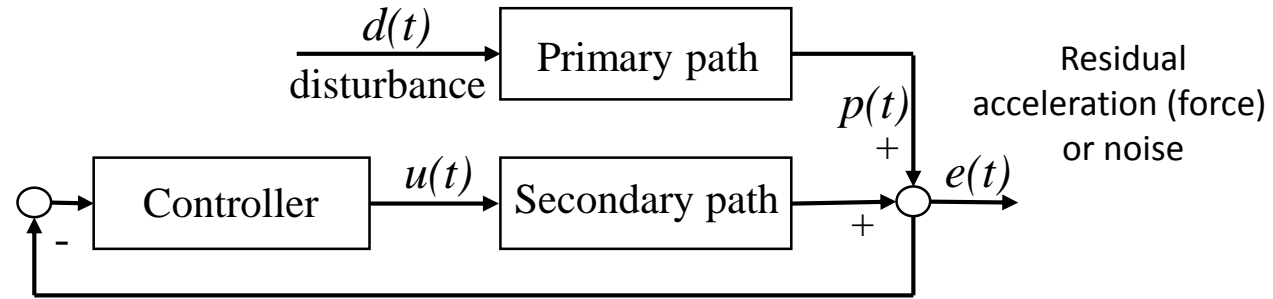


- The disturbances are unknown and time varying
- The « plant » has almost constant dynamic characteristics (in most of the applications)

Adaptive Regulation Problem

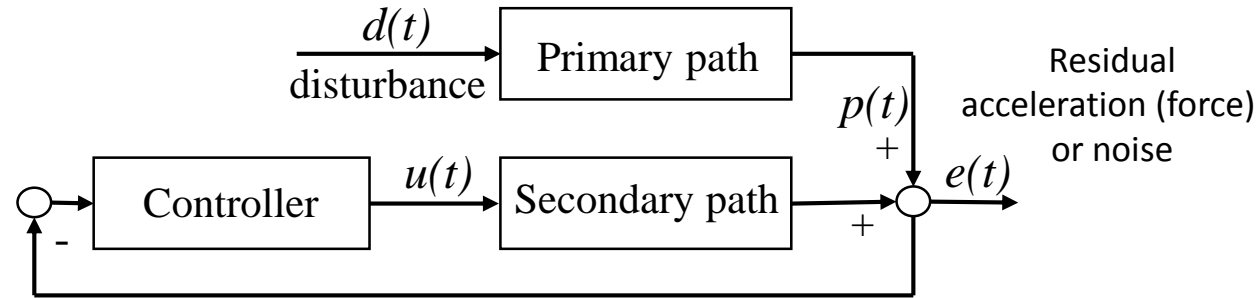
Basic Control Configurations in ANC and AVC

Feedback configuration

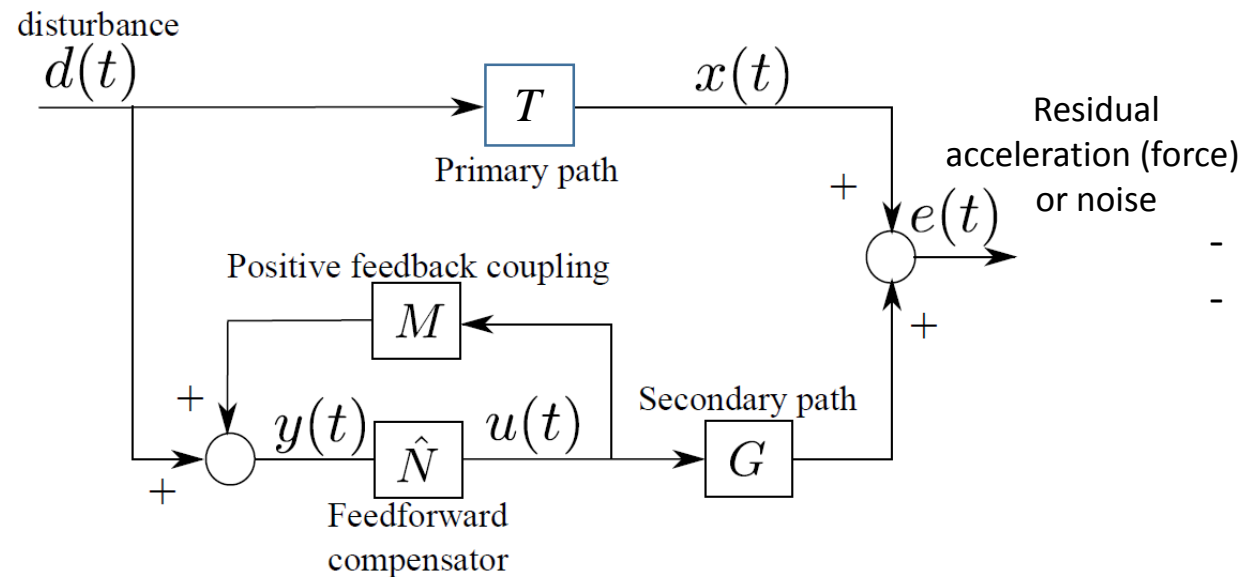


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Feedforward configuration

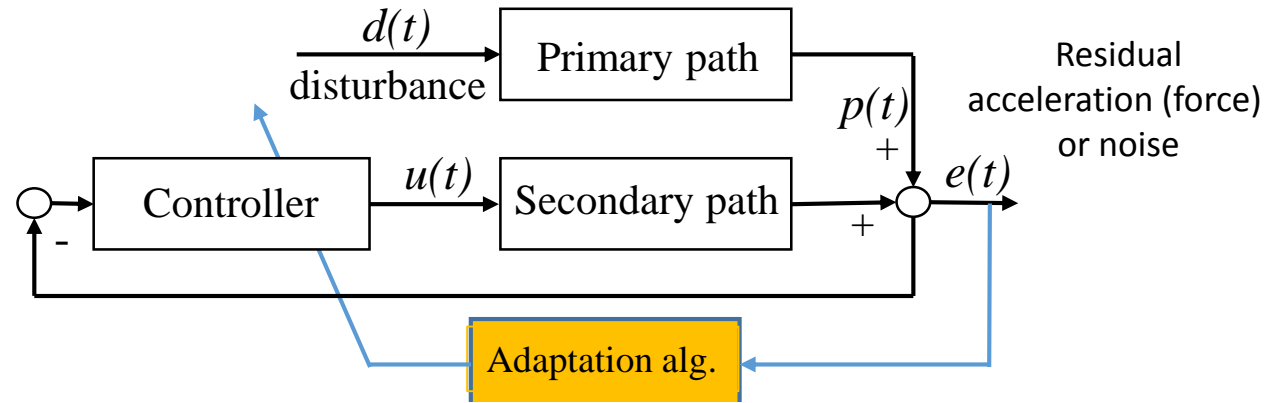


- Requires an additional sensor
- Internal positive feedback

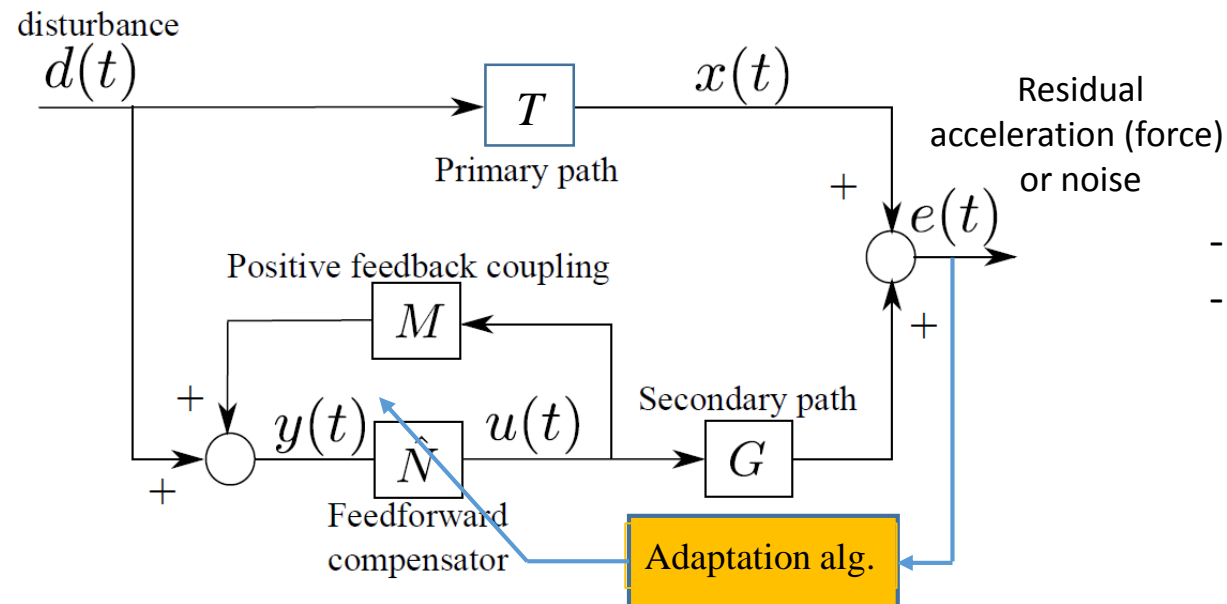
Do as much as possible by **feedback** (limitations due to Bode Integral) and then add **feedforward compensation**

Basic Control Configurations in ANC and AVC

Feedback configuration



Feedforward configuration

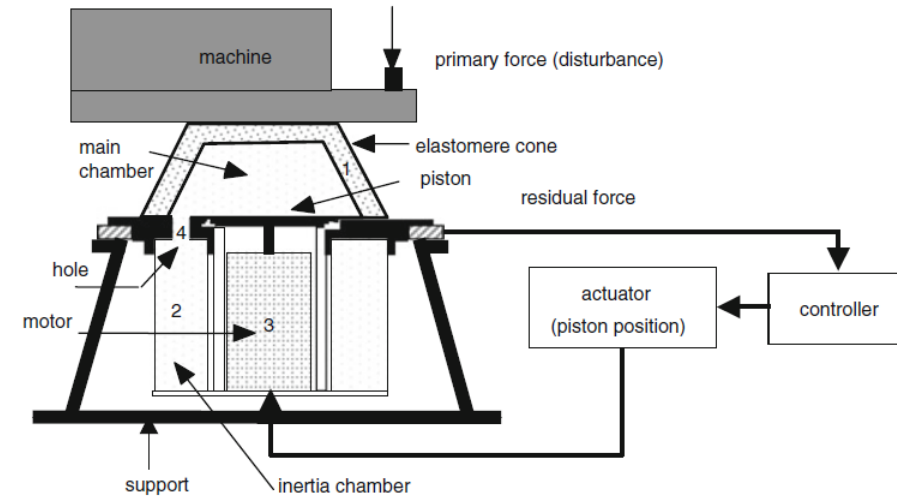
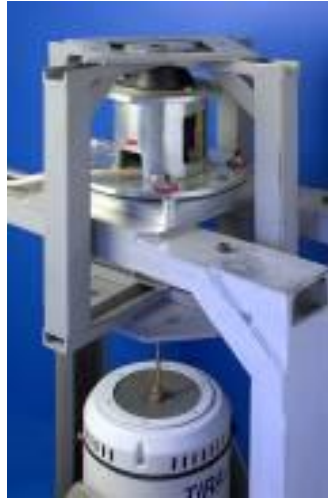


- Requires an additional sensor
- Internal positive feedback

Variability of the disturbance characteristics requires the use of an adaptive approach

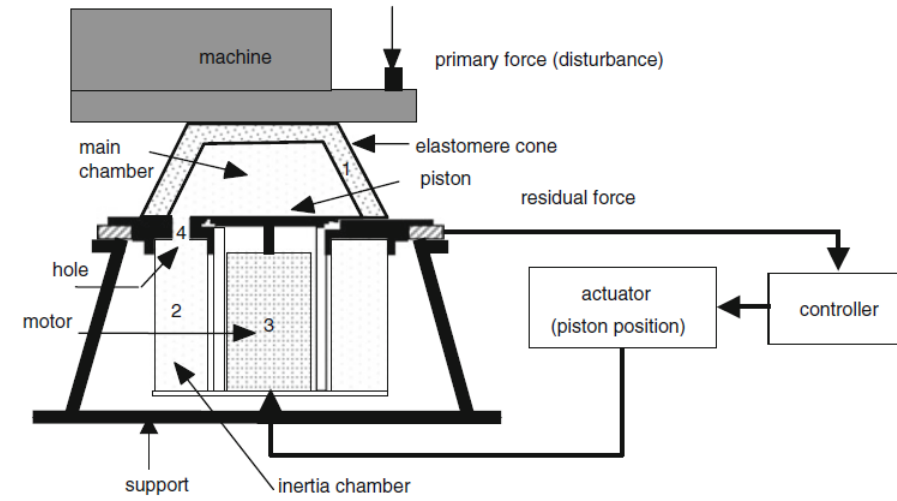
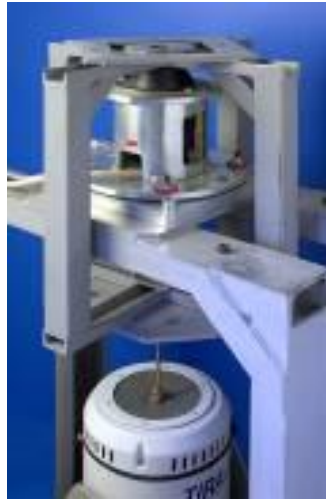
Some examples in AVC (1)

Active suspension

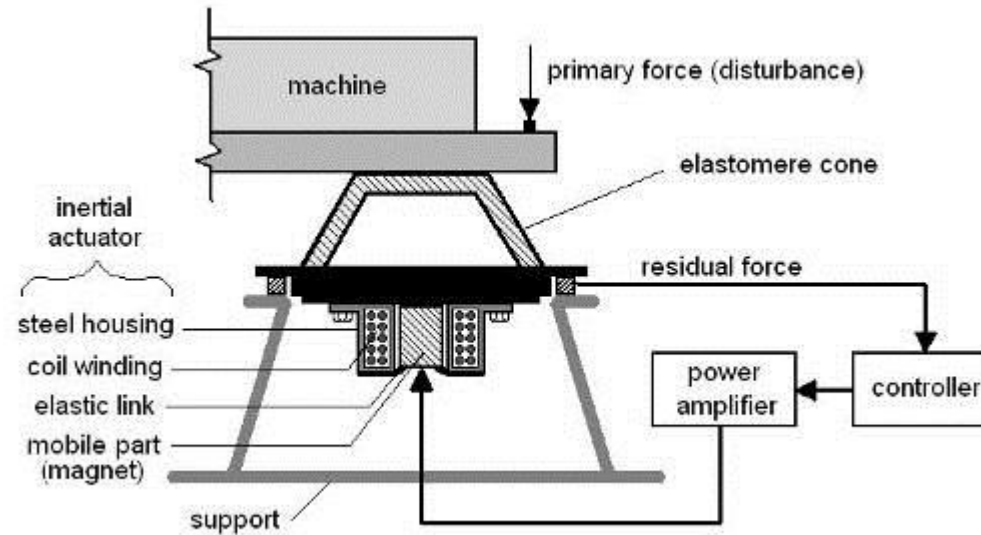
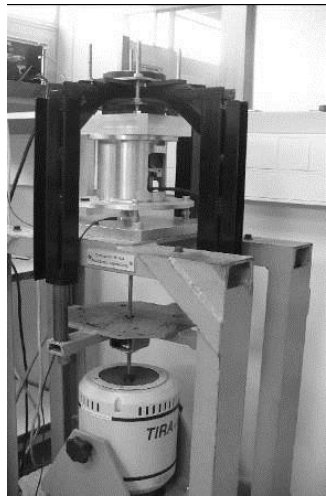


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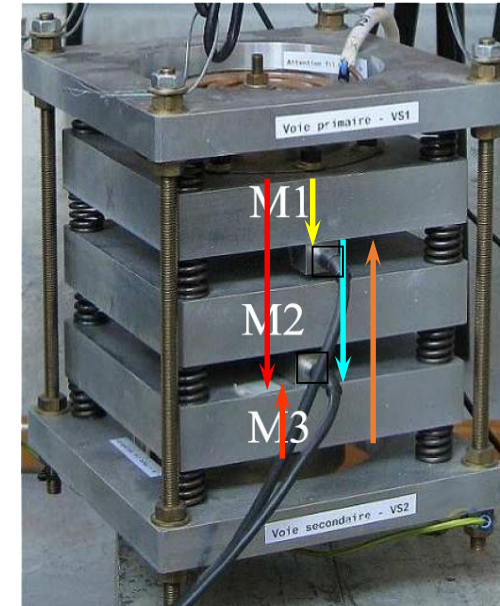
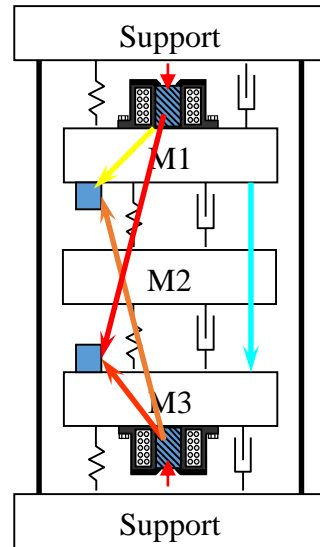
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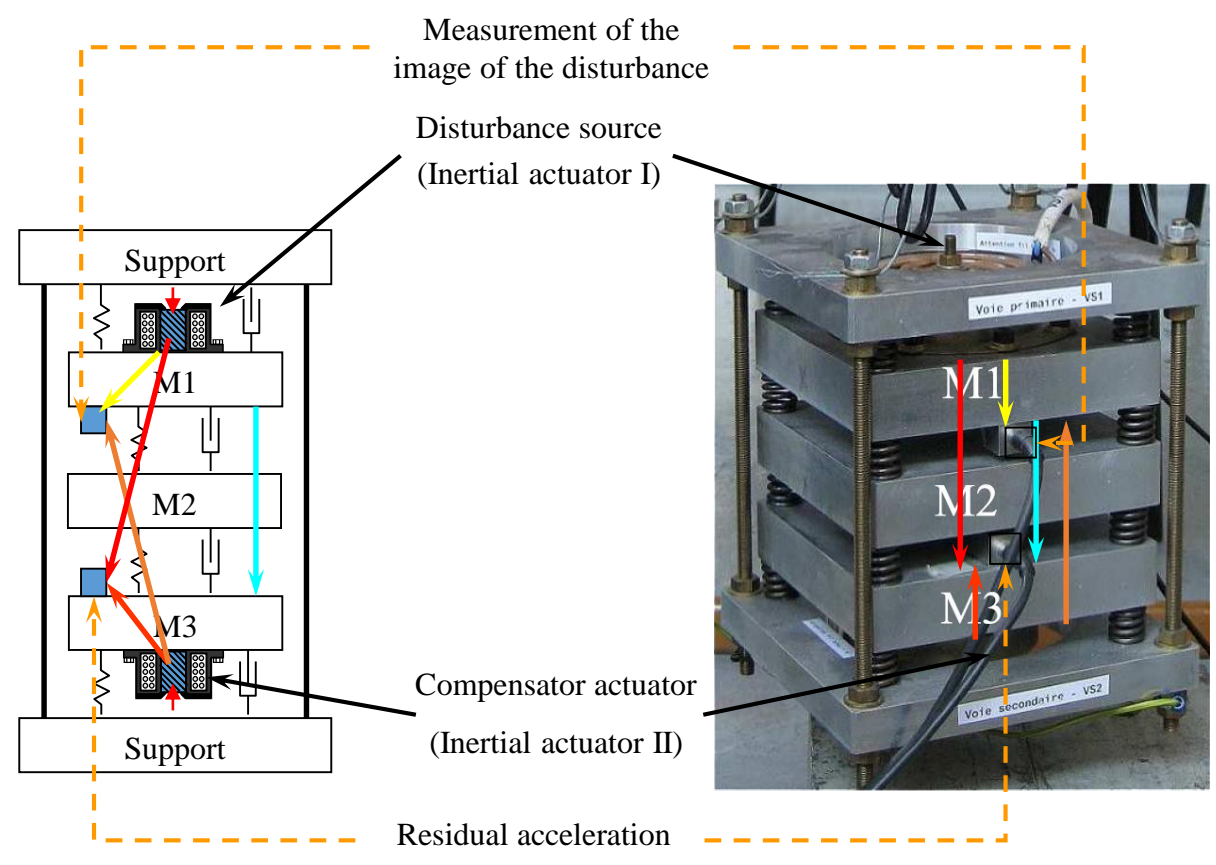
Inertial actuator



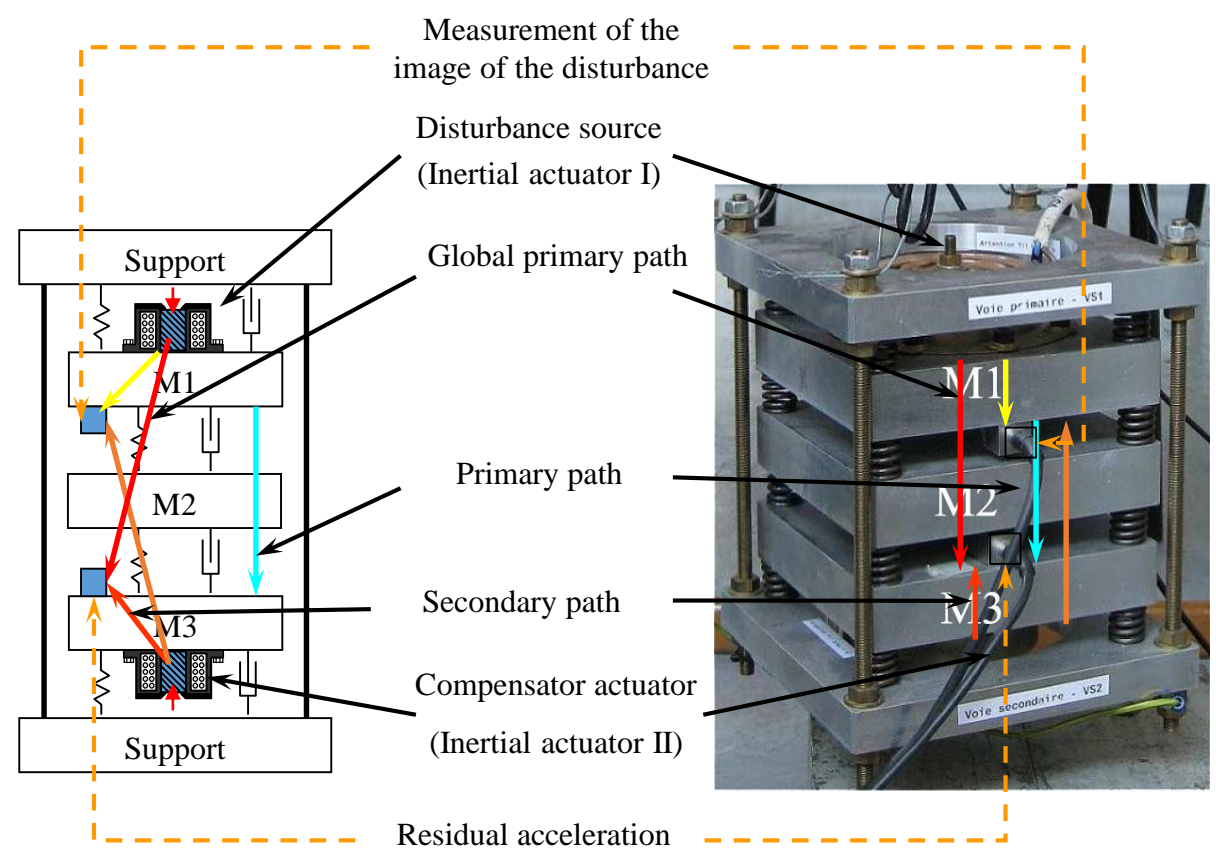
Some examples in AVC (2)



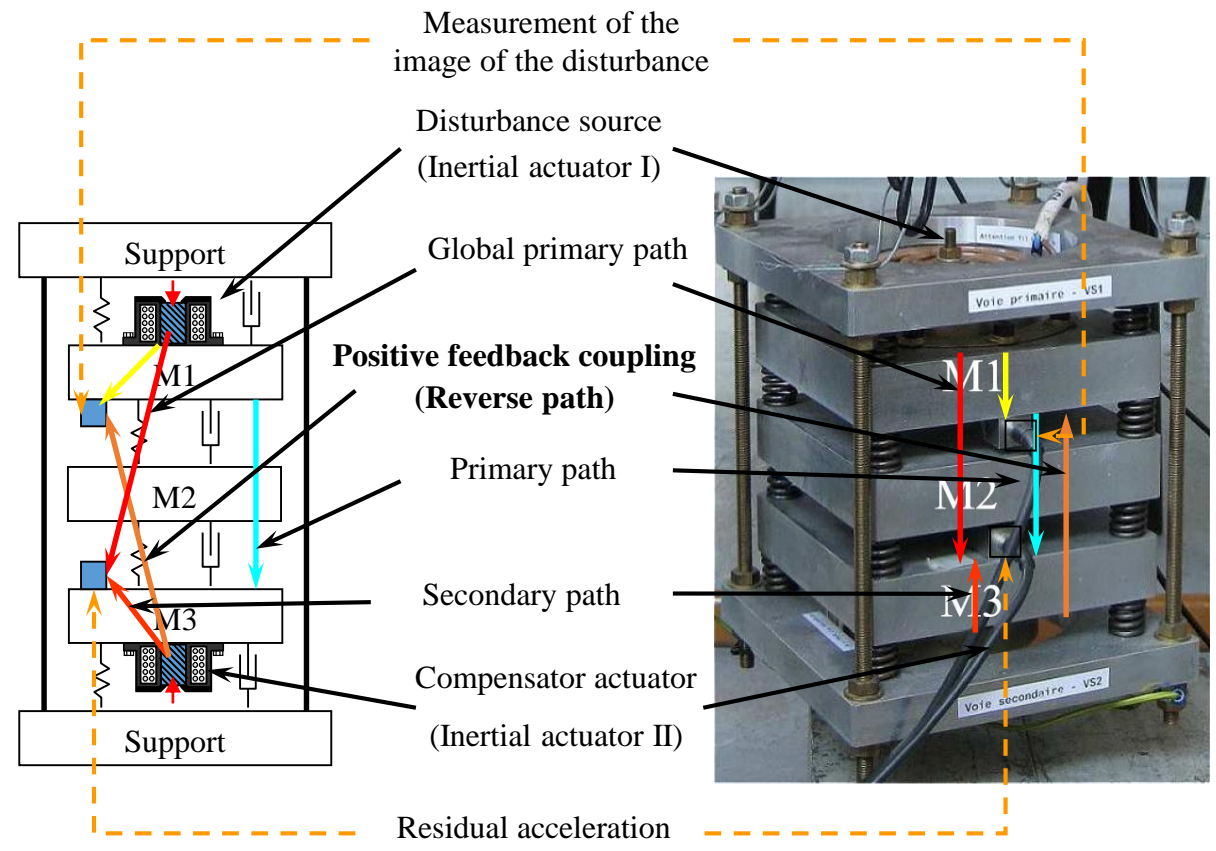
Some examples in AVC (2)



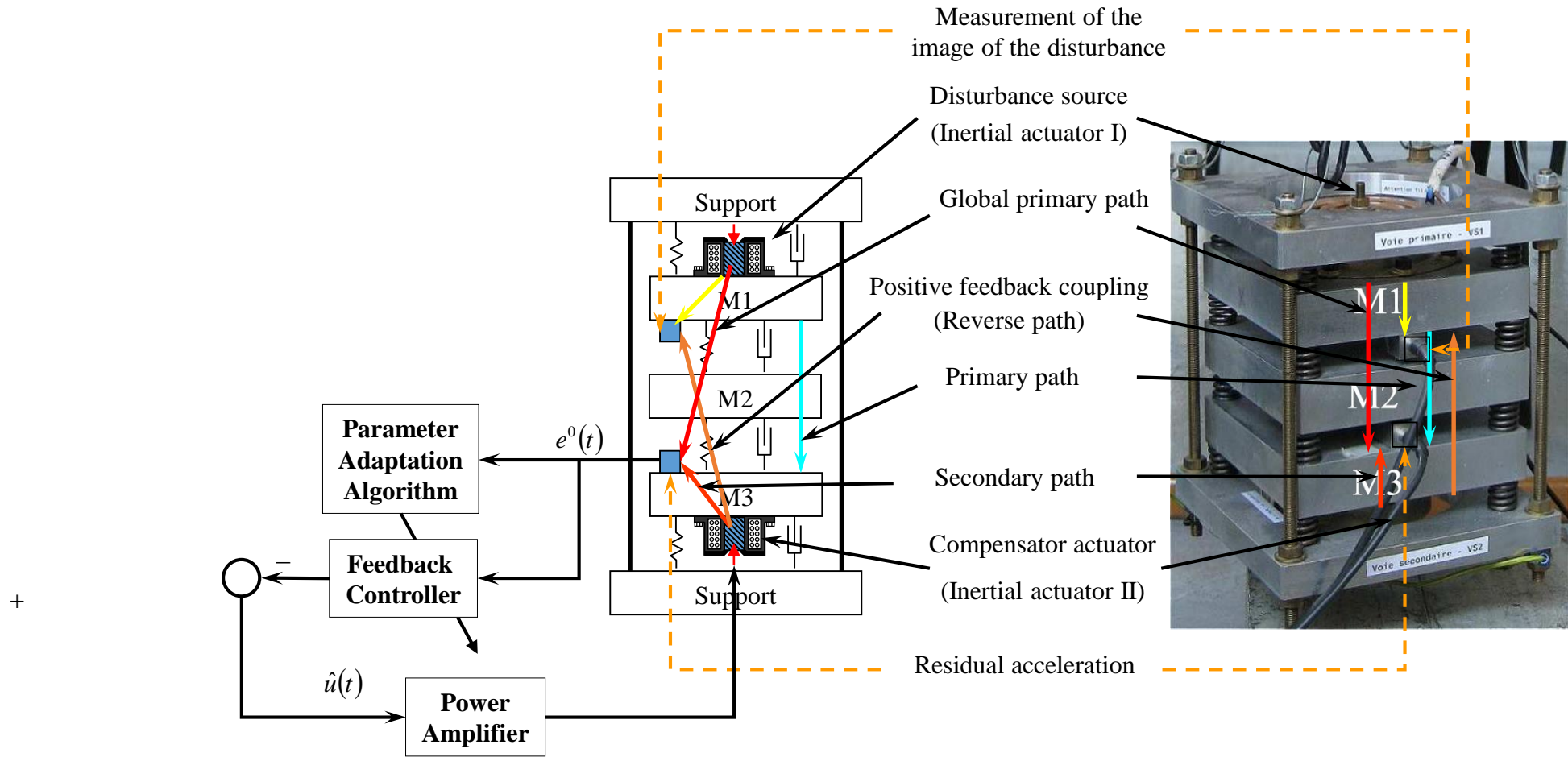
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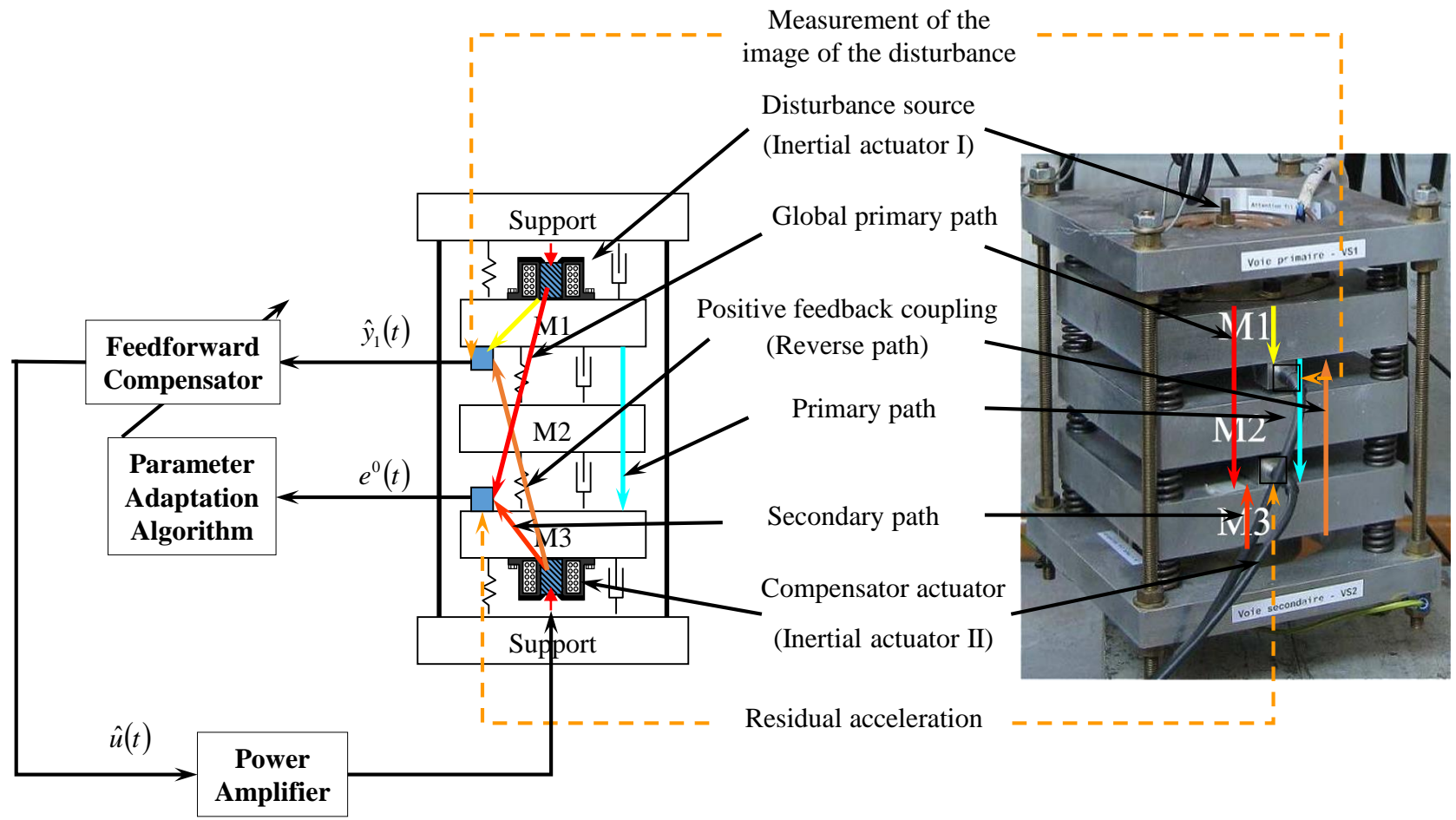


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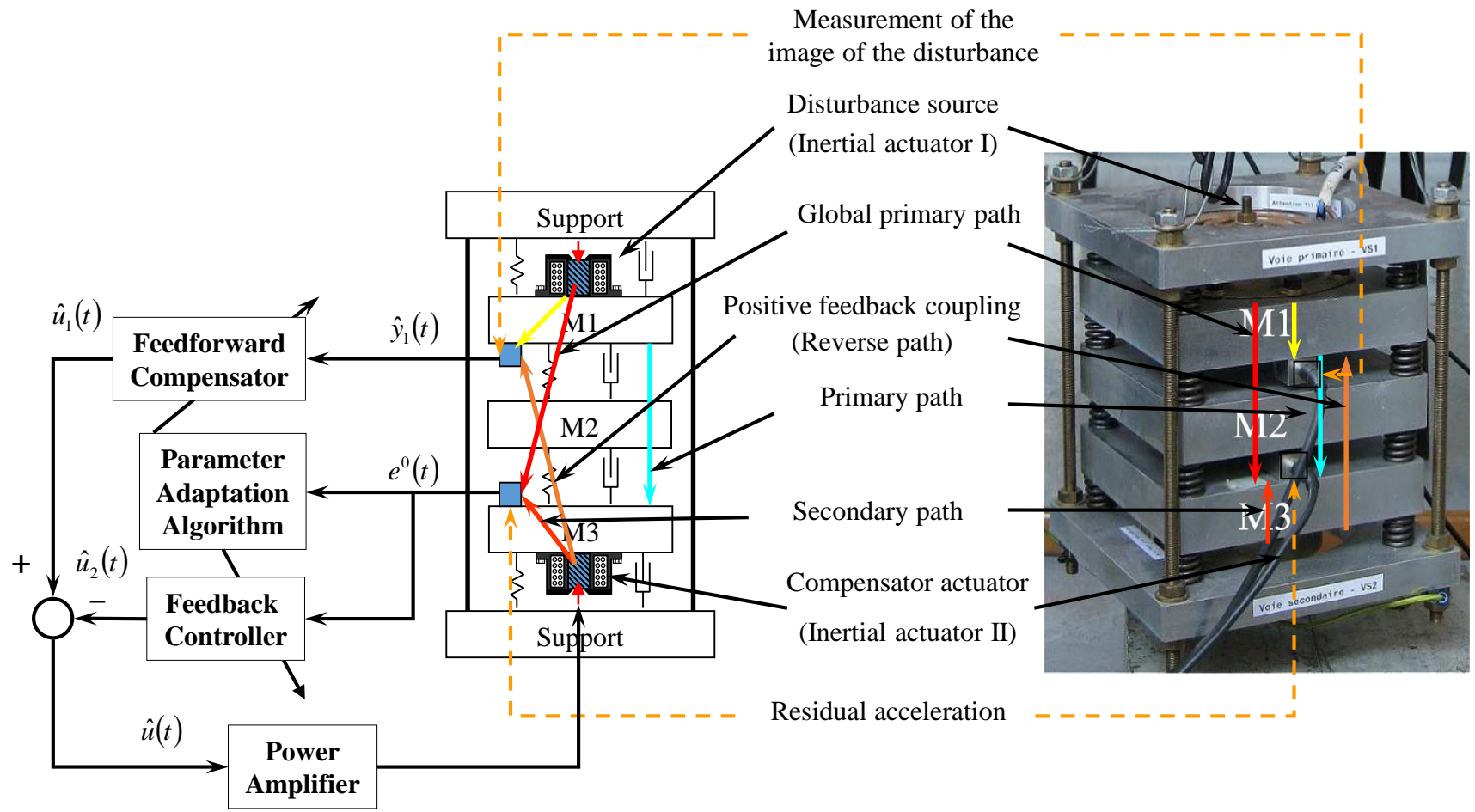
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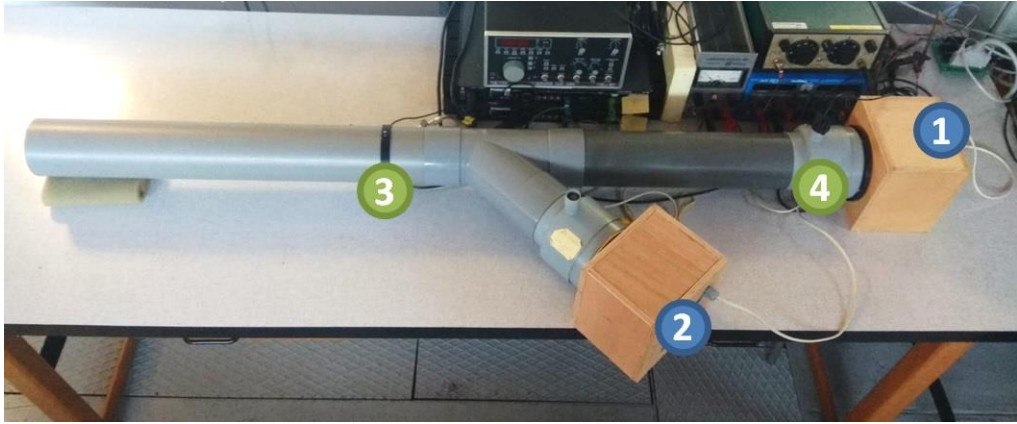


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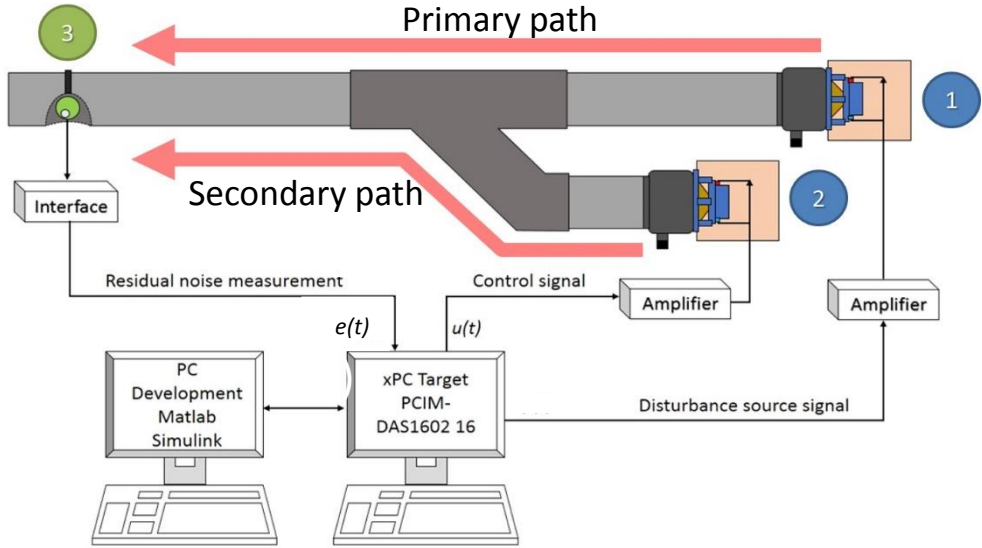
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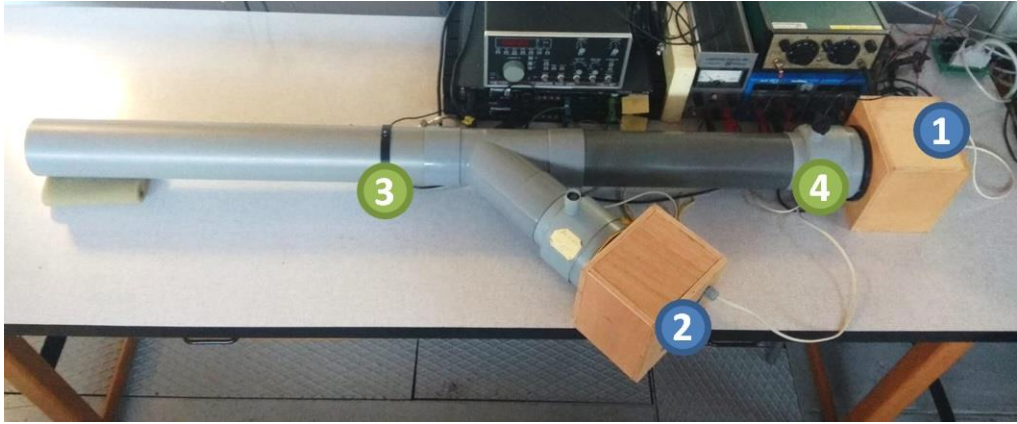
An example in ANC (silencer)



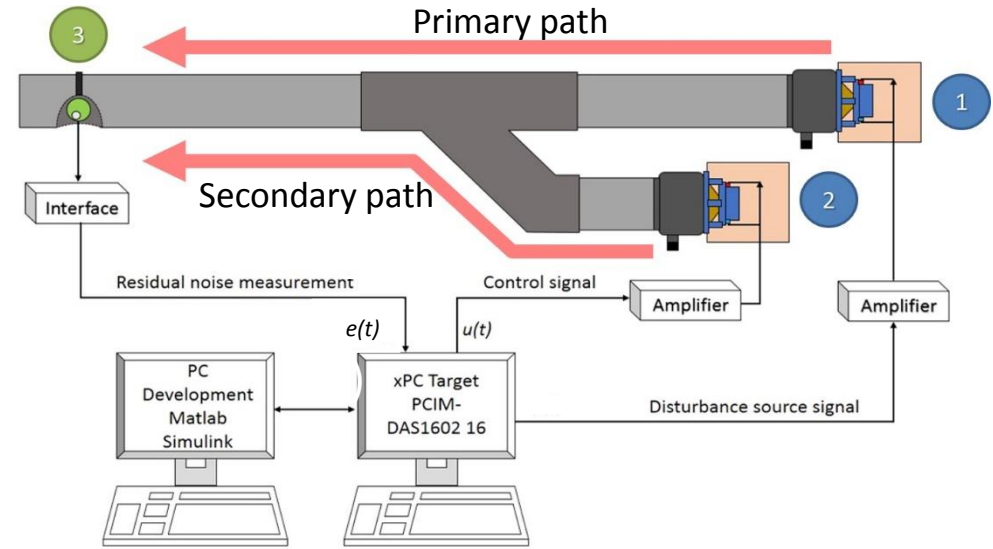
Feedback Configuration



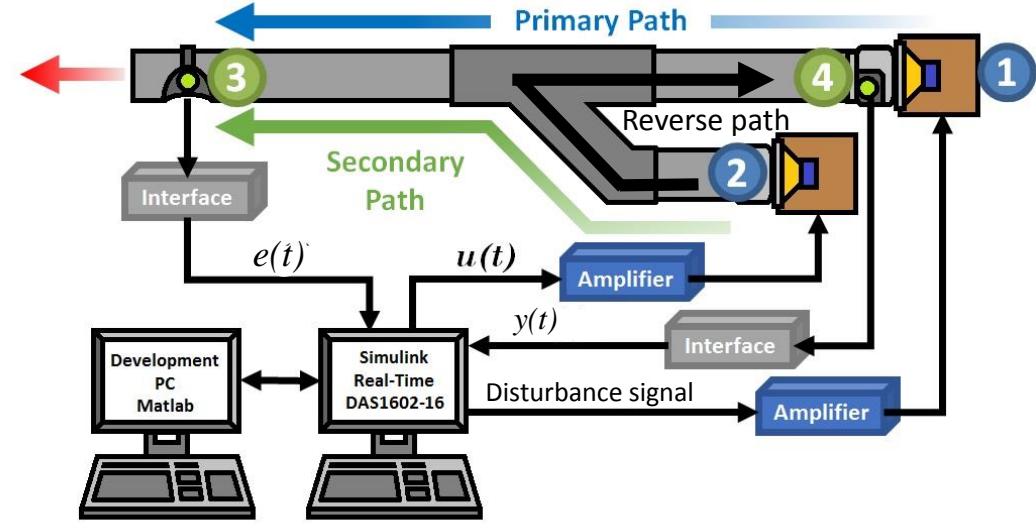
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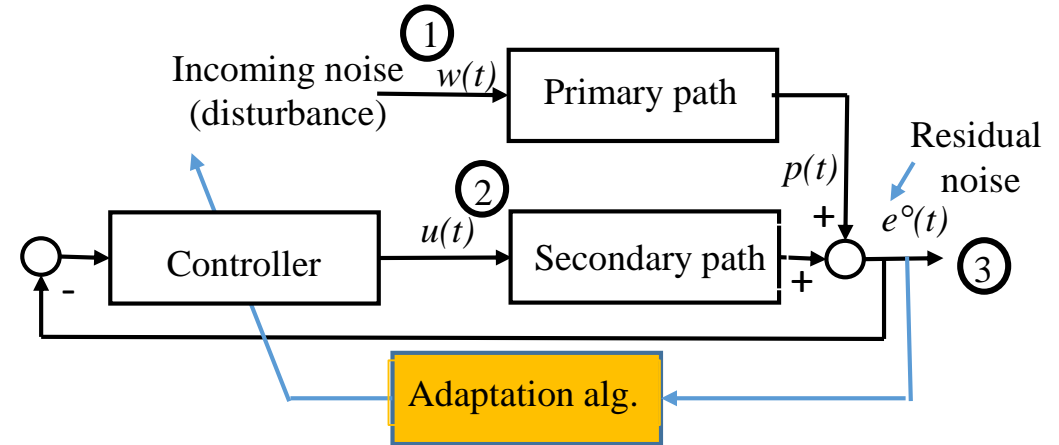
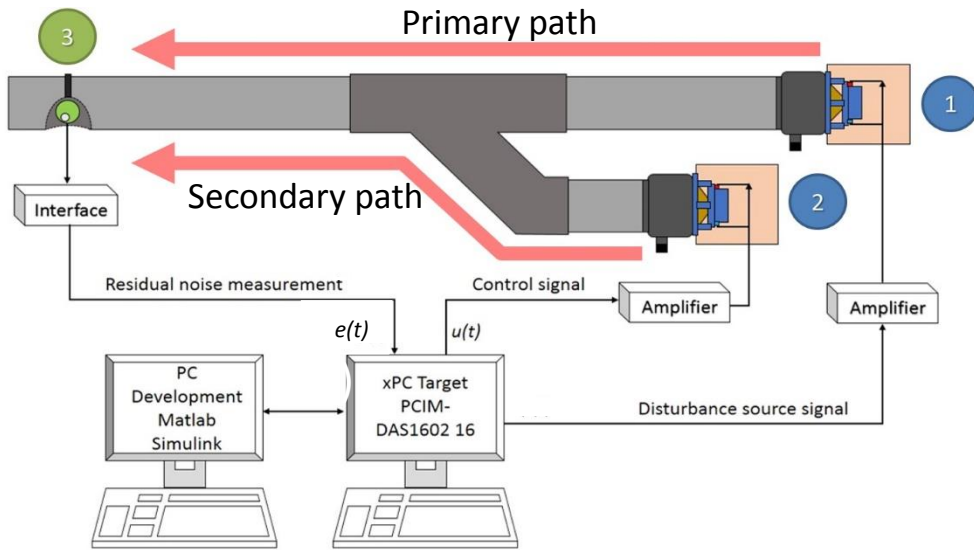
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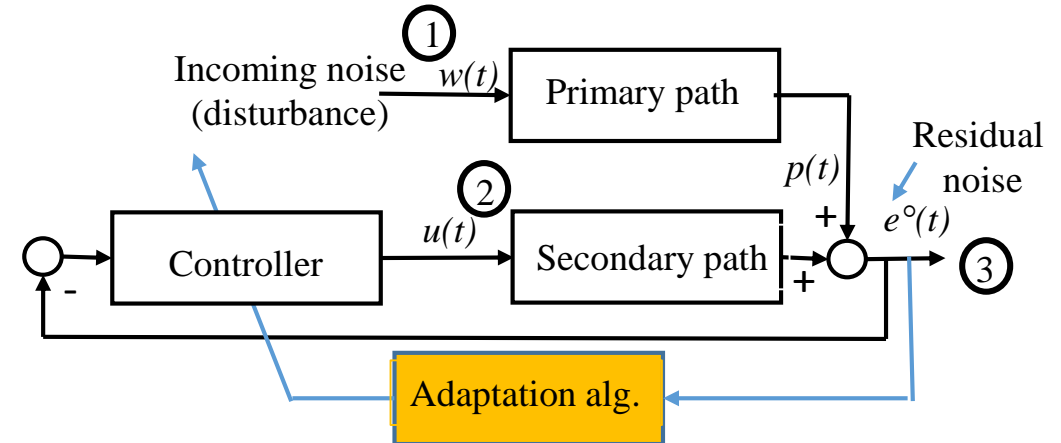
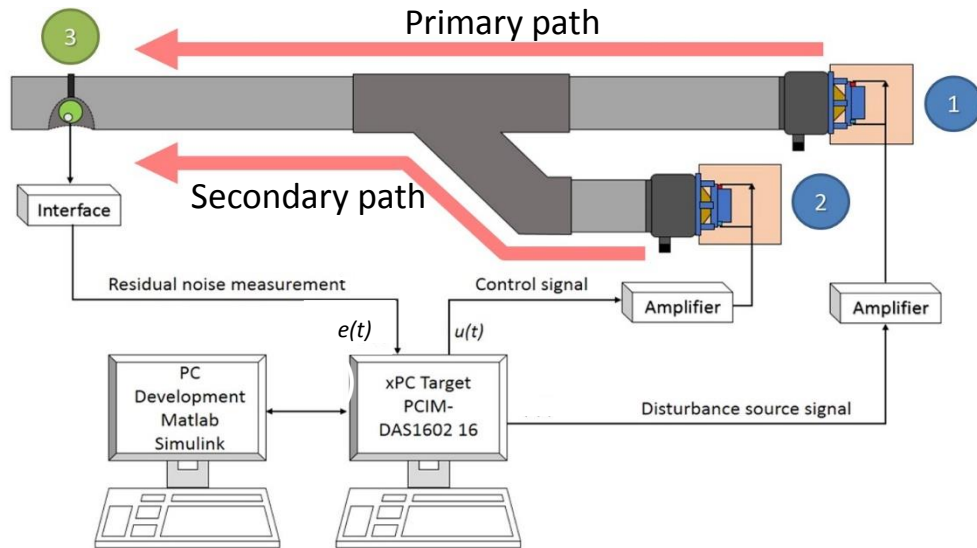


Adaptive feedback noise attenuation



Type of disturbance: Multiple tonal (narrow band) noise with unknown and time varying characteristics

Adaptive feedback noise attenuation

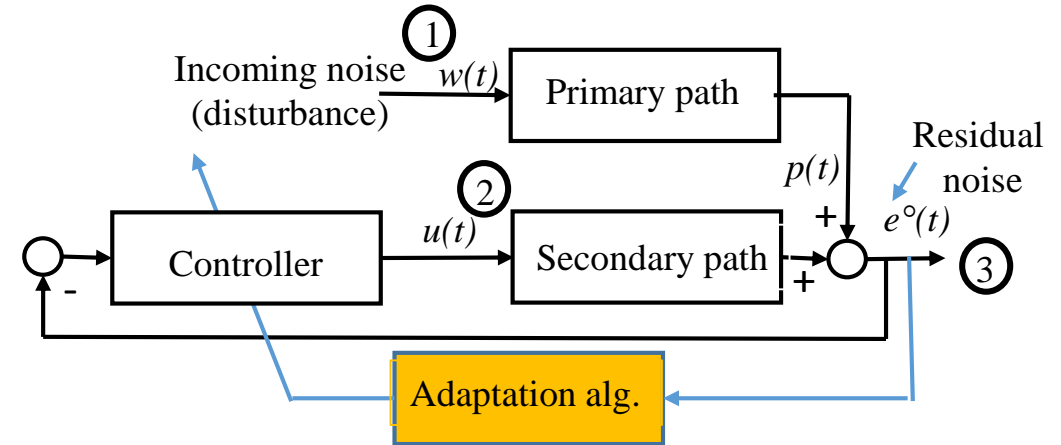
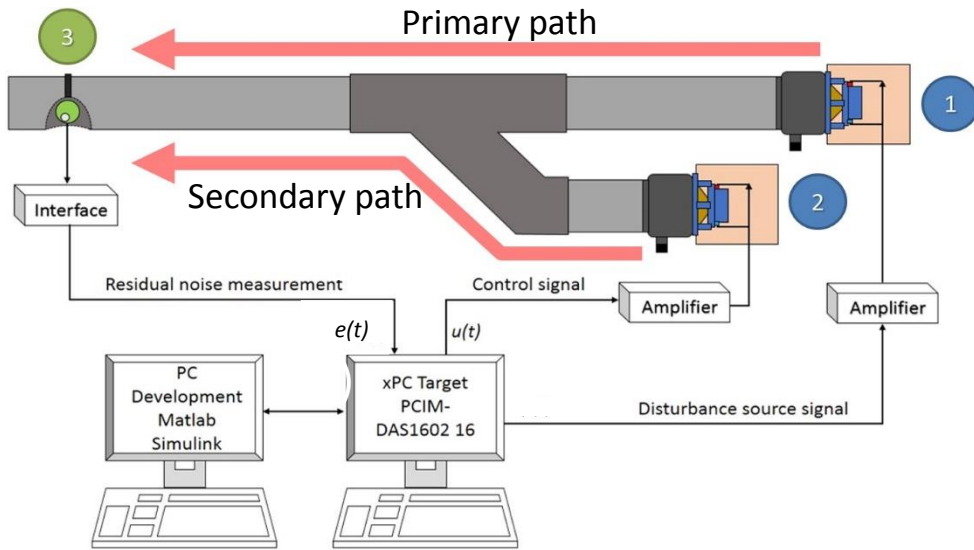


Type of disturbance: Multiple tonal (narrow band) noise with unknown and time varying characteristics

Challenges

- Removing the need for an additional microphone
- What control strategy for cancelling this type of disturbance?
- Could we use a « direct » adaptation scheme?
(to avoid explicit identification of the disturbance model and computation of the controller at each sampling)

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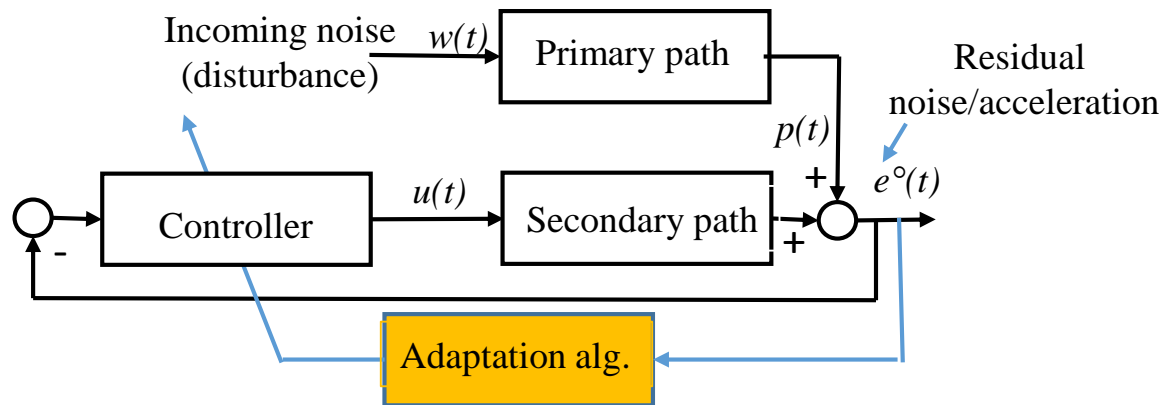
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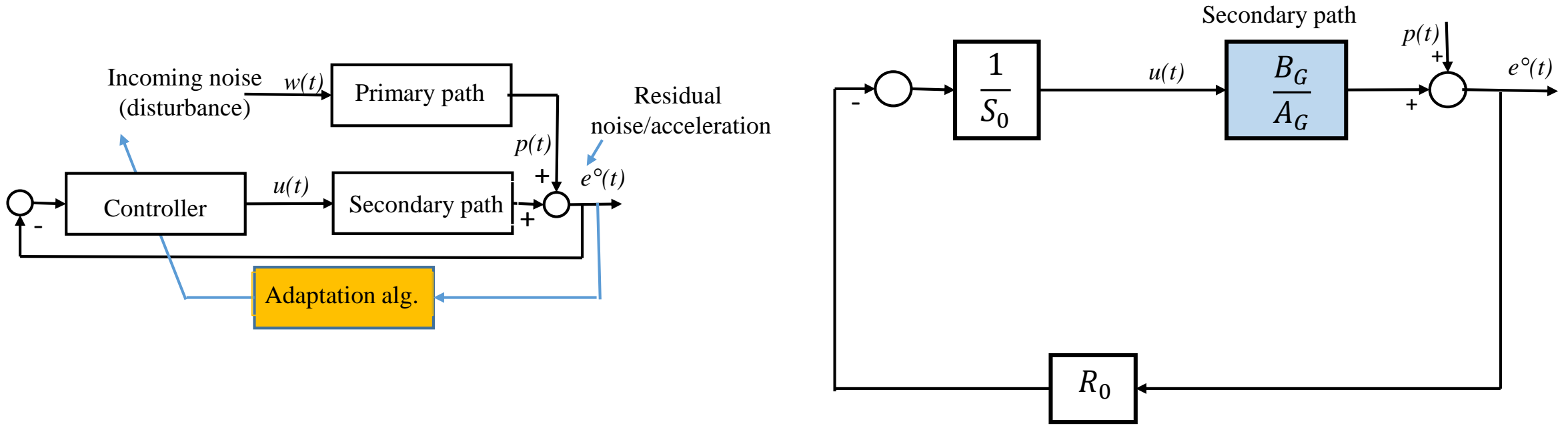
Answers:

- 1) Feedback
- 2) Internal model principle
- 3) Youla-Kucera parametrization of the controller

Adaptive YK Feedback attenuation of narrow band noise (or vibration)



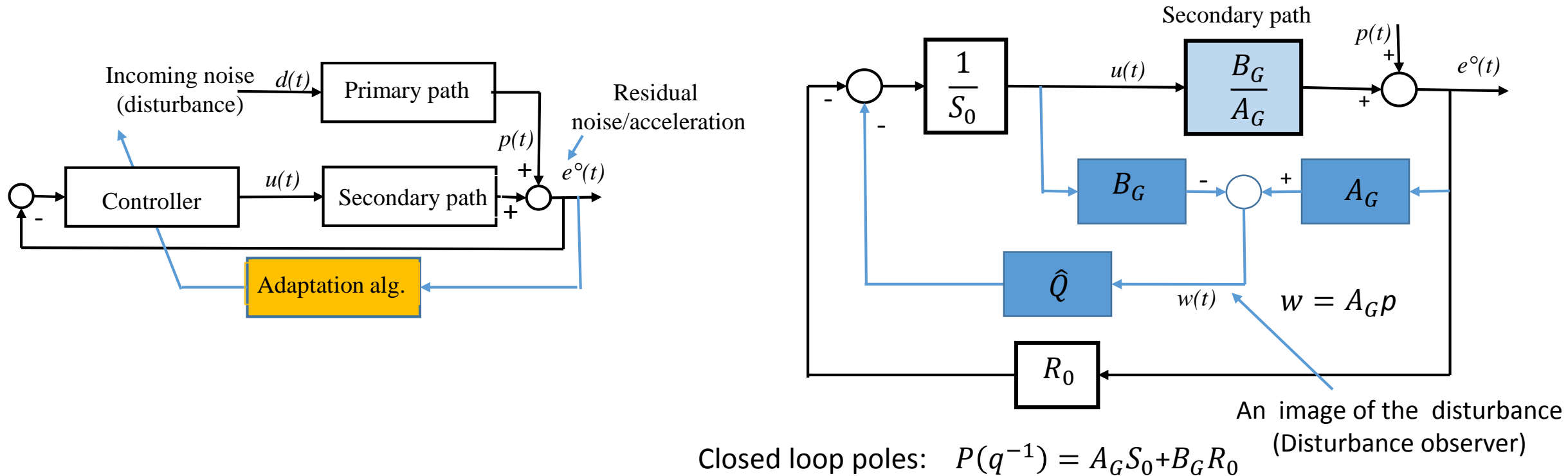
Adaptive YK Feedback attenuation of narrow band noise (or vibration)



Closed loop poles: $P(q^{-1}) = A_G S_0 + B_G R_0$

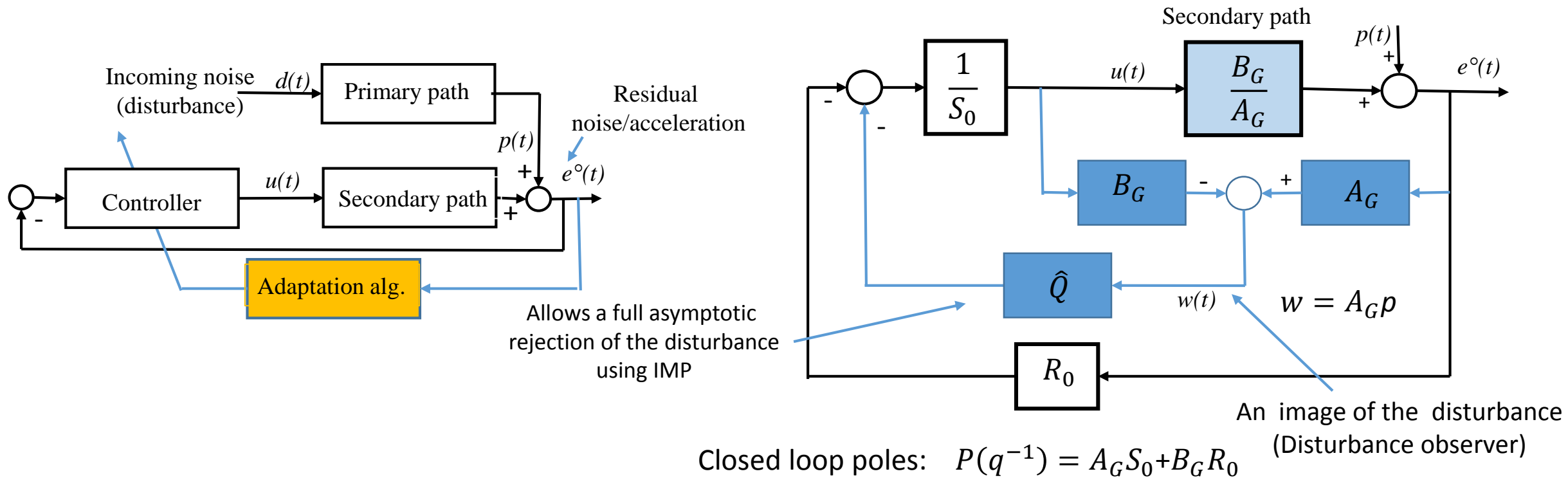
- Secondary path is characterized by a high order model (30 to 70 parameters)

Adaptive YK Feedback attenuation of narrow band noise (or vibration)



- Secondary path is characterized by a high order model (30 to 70 parameters)
- Q is a FIR filter
- **Poles of the closed loop remain unchanged independently of the parameters of Q**

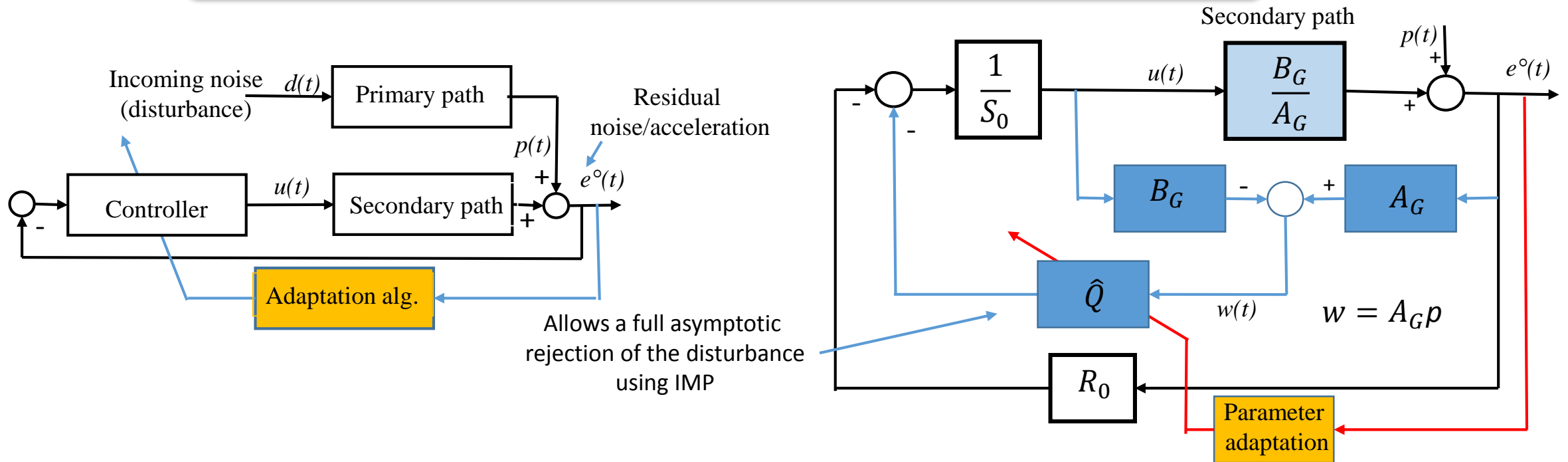
Adaptive YK Feedback attenuation of narrow band noise (or vibration)



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- Based on the Internal Model Principle (the controller should contain the model of the disturbance)

N sinusoids: order of Q=2N

Adaptive YK Feedback attenuation of narrow band noise (or vibration)



- Q is a FIR filter
- **Poles of the closed loop remain unchanged independently of the parameters of Q**
- Based on the internal model principle (the controller should contain the model of the disturbance)
- N sinusoids: order of Q=2N
- ***Extremely fast adaptation,***

Direct adaptive feedback regulation

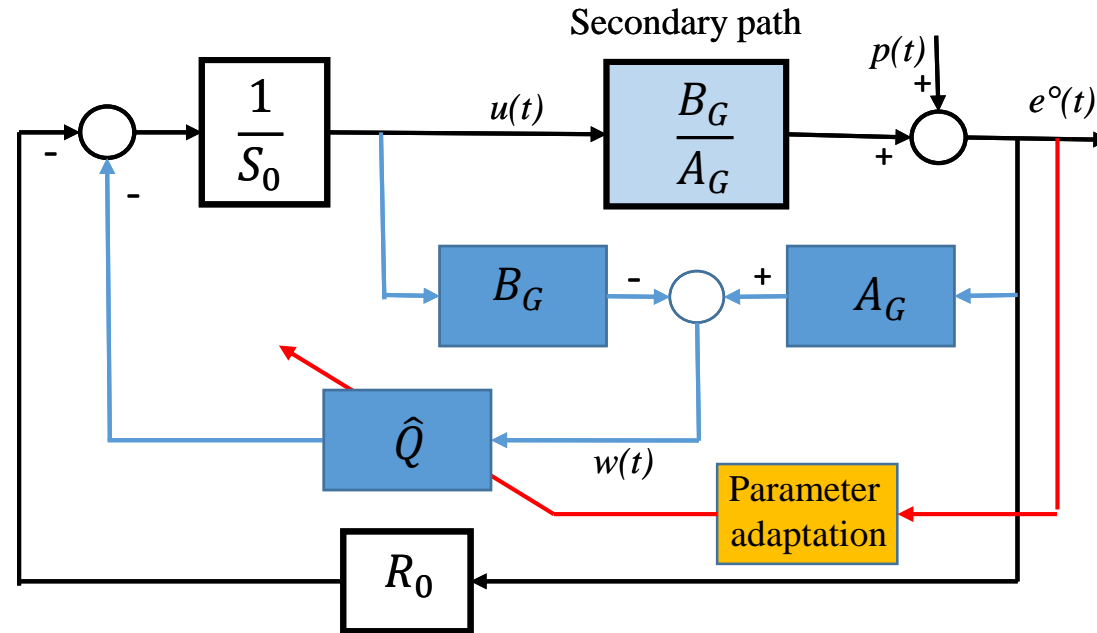
Most important:

YK parametrization allows to express the measured residual error ($e^\circ(t)$) as a function of the errors in the Q parameters (with respect to the optimal ones)

$$e^\circ(t+1) = [Q(q^{-1}) - \hat{Q}(t, q^{-1})] \cdot \frac{q^{-d} B_G^*(q^{-1})}{P(q^{-1})} \cdot w(t) + x(t+1)$$

← Vanishing term

Consequence:
A direct adaptive regulation scheme can be built



Direct adaptive feedback regulation

Most important:

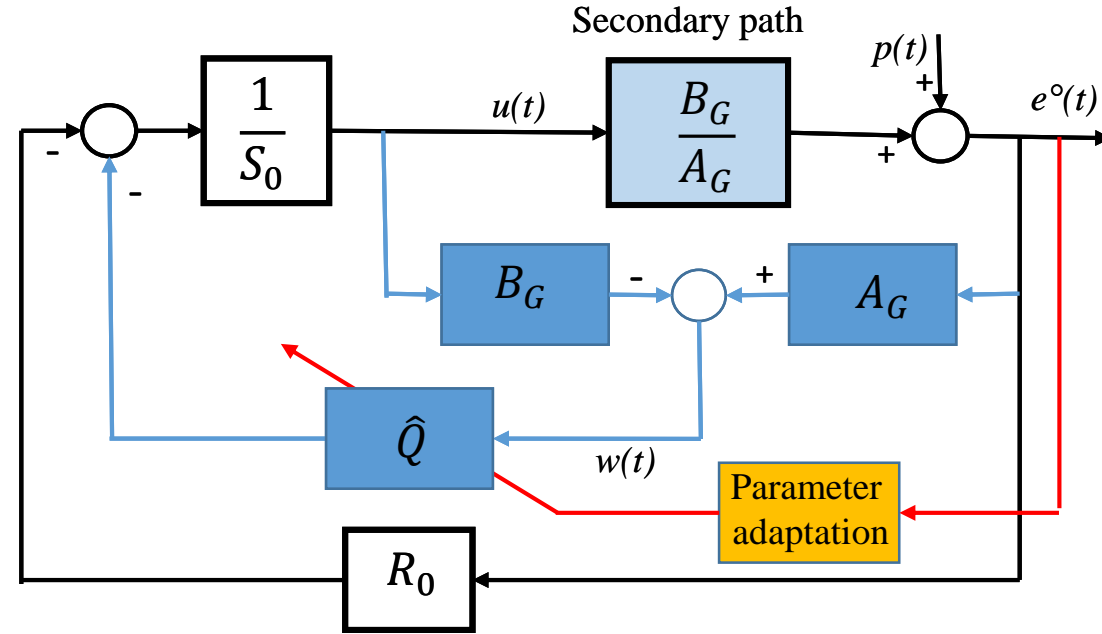
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- *The order of the Q polynomial depends upon the order of the disturbance model denominator (D_p) and not upon the complexity of the plant model*
- Particularly dedicated to multiple narrow band disturbances or limited band disturbances (Bode limitations)

Direct adaptive feedback regulation

Most important:

YK parametrization allows to express the measured residual error ($e^o(t)$) as a function of the errors in the Q parameters with respect to the optimal ones

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Consequence:

A direct adaptive regulation scheme can be built

$$\theta = [q_1, q_2, \dots] ; \hat{\theta}(t) = [\hat{q}_1(t), \hat{q}_2(t) \dots]$$

$$\phi(t) = [w(t), w(t-1) \dots]$$

$$L(q^{-1}) = q^{-d} B_G^* / P$$

$$\psi(t) = L(q^{-1}) \phi(t)$$

$$e^o(t+1) = [\theta - \hat{\theta}(t)]^T \psi(t)$$

Direct adaptive feedback regulation

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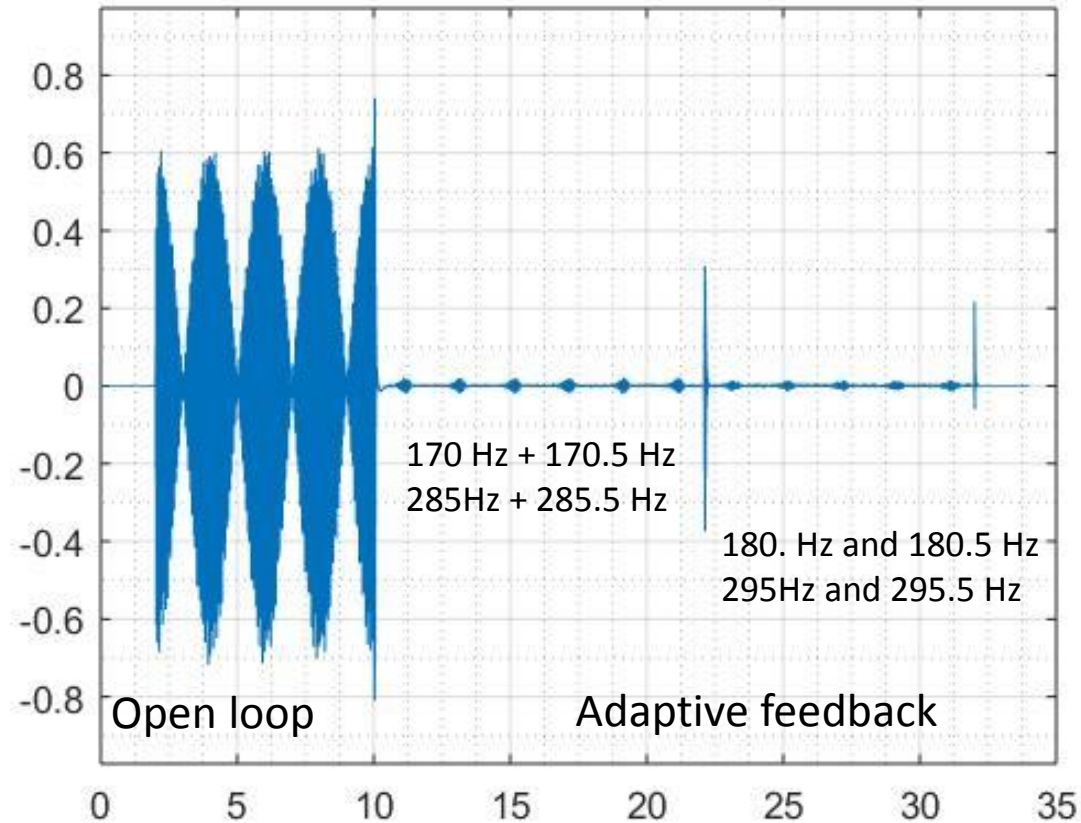
$$e(t+1) = [\theta - \hat{\theta}(t+1)]^T \psi(t)$$

← Standard form for the synthesis of stable adaptive schemes

- Performance will depend of course also upon the design of the parameter adaptation algorithms

Adaptive Attenuation of Acoustical Interference

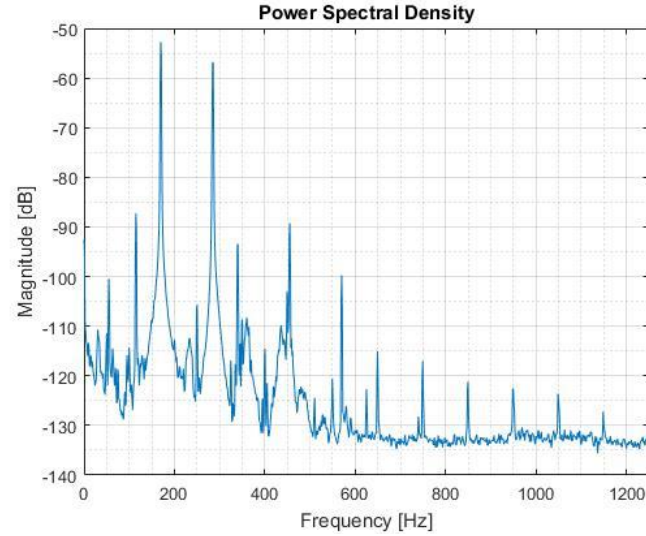
Nominal frequencies: 1) 170 Hz and 170.5 Hz + 2) 285 Hz and 285.5 Hz
Variations of + 10 Hz for the nominal frequencies
YK adaptive feedback



Attenuation of 2 simultaneous tonal noises

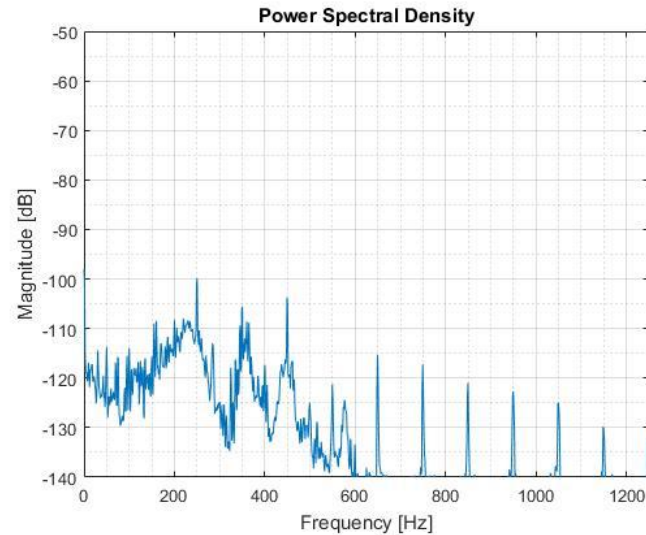
Noise Frequencies : 170 Hz and 285 Hz

Open loop

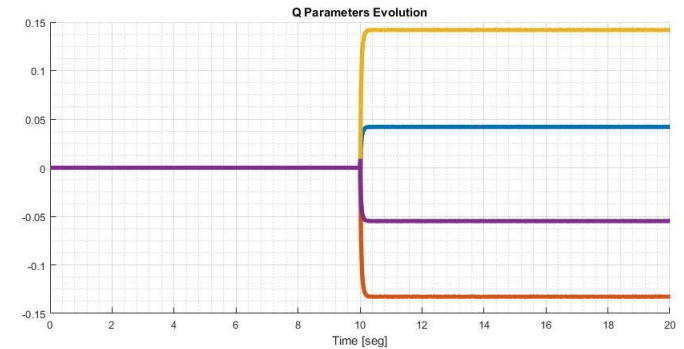


Adaptive feedback

Global Attn.: 89.5 dB
Attn. 170 Hz: 60 dB
Attn. 285 Hz: 55.9 dB



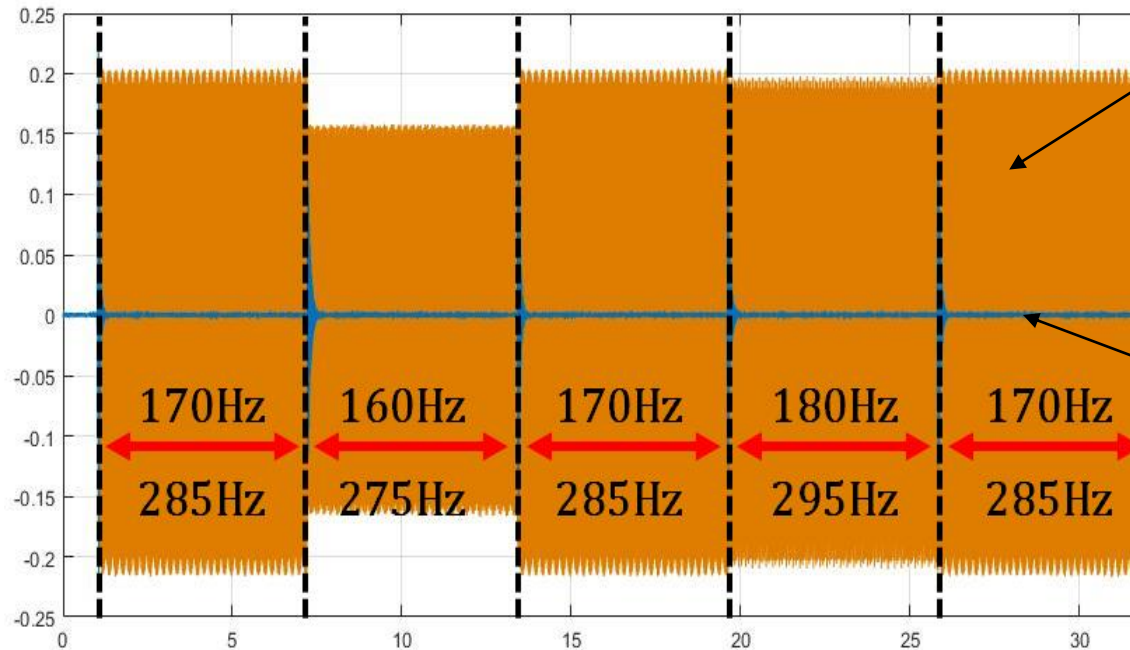
Evolution of the Q parameters



Step Changes in Noise Frequencies

Nominal frequencies: 170 Hz and 285 Hz

Step changes: +/- 10 Hz



Open loop

Adaptive feedback

Open loop

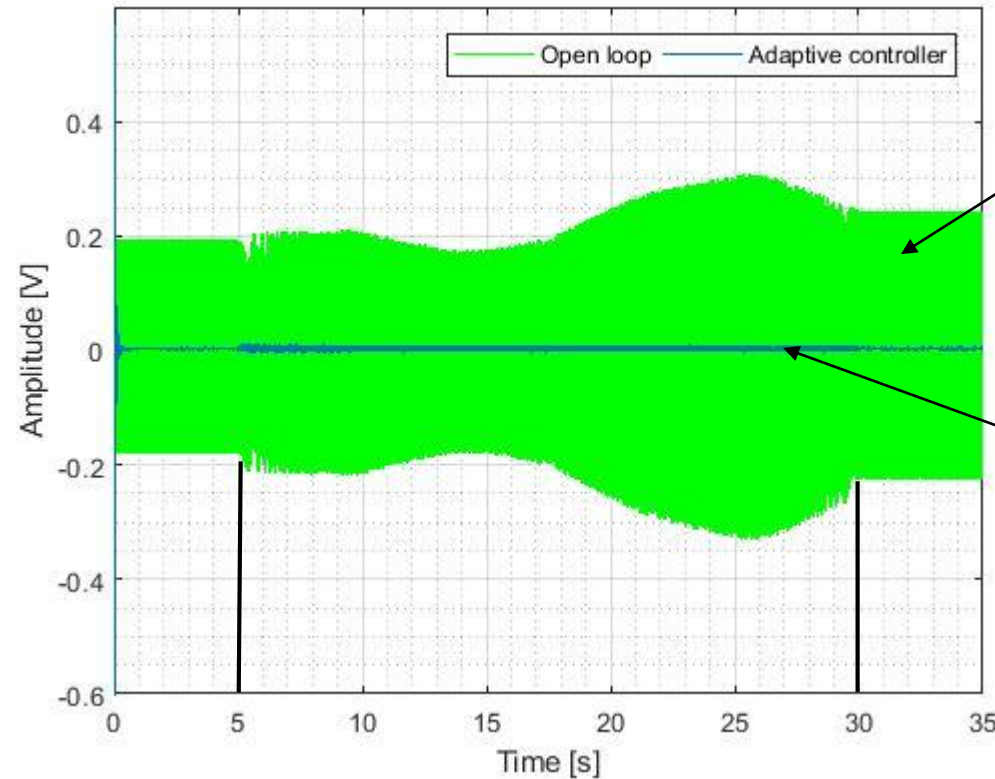


Adaptive feedback



Chirp frequency variation of 2 simultaneous tonal disturbances

1) From 100 Hz to 200 Hz + 2) From 200 Hz to 300 Hz (from 5s to 30s)



Open loop

Adaptive feedback

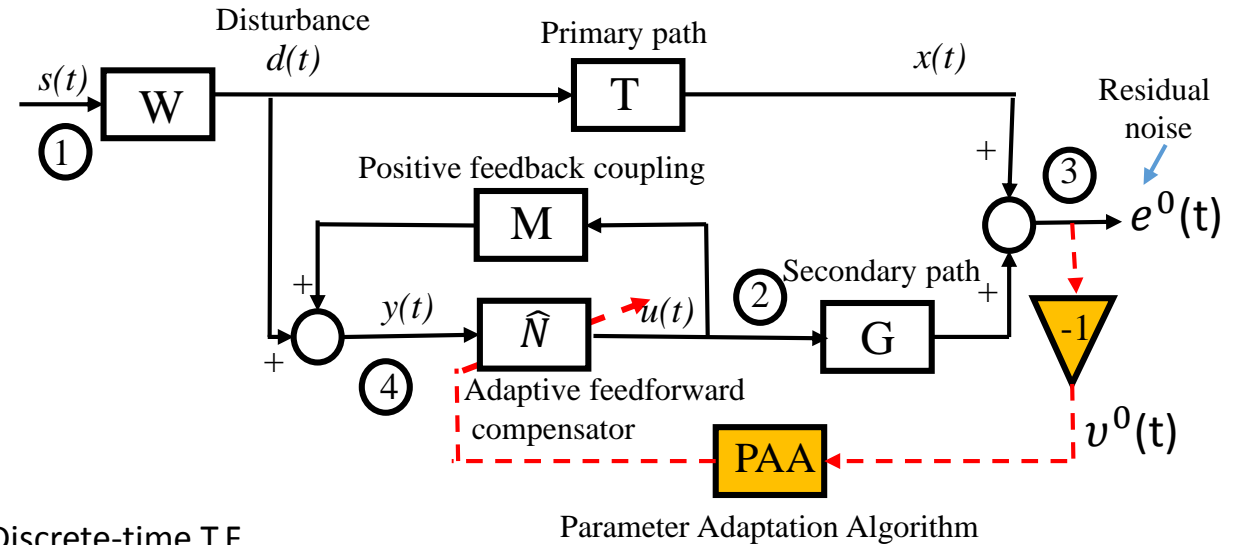
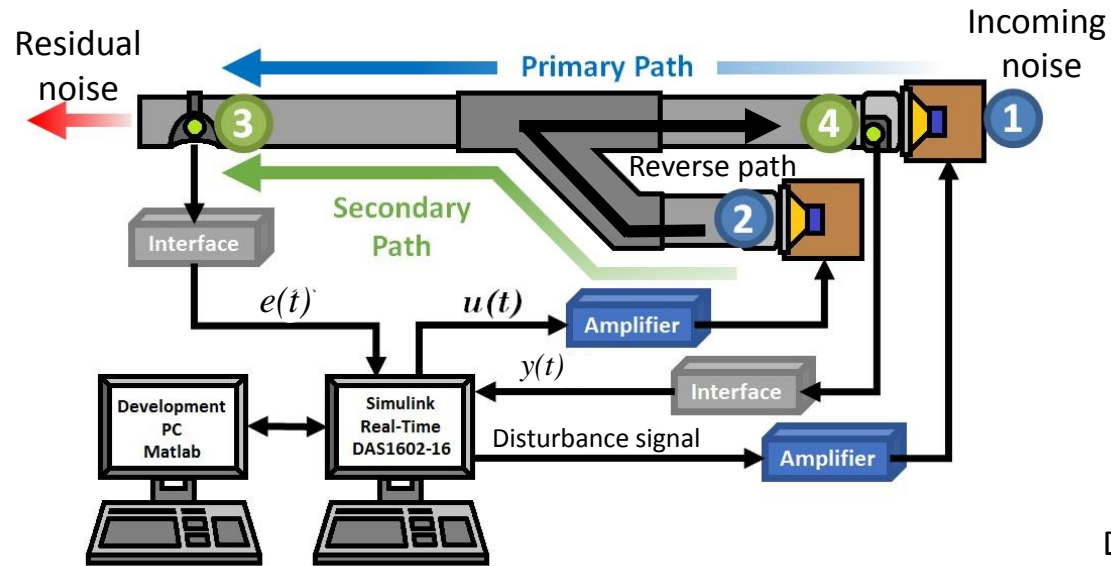
Open loop



Adaptive feedback



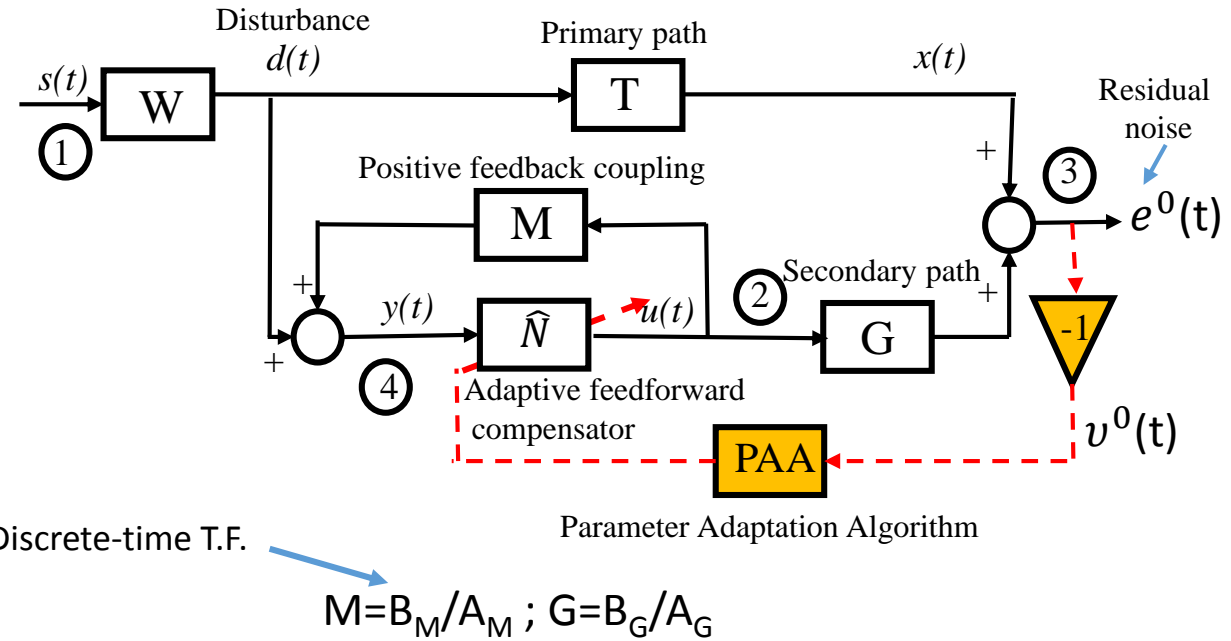
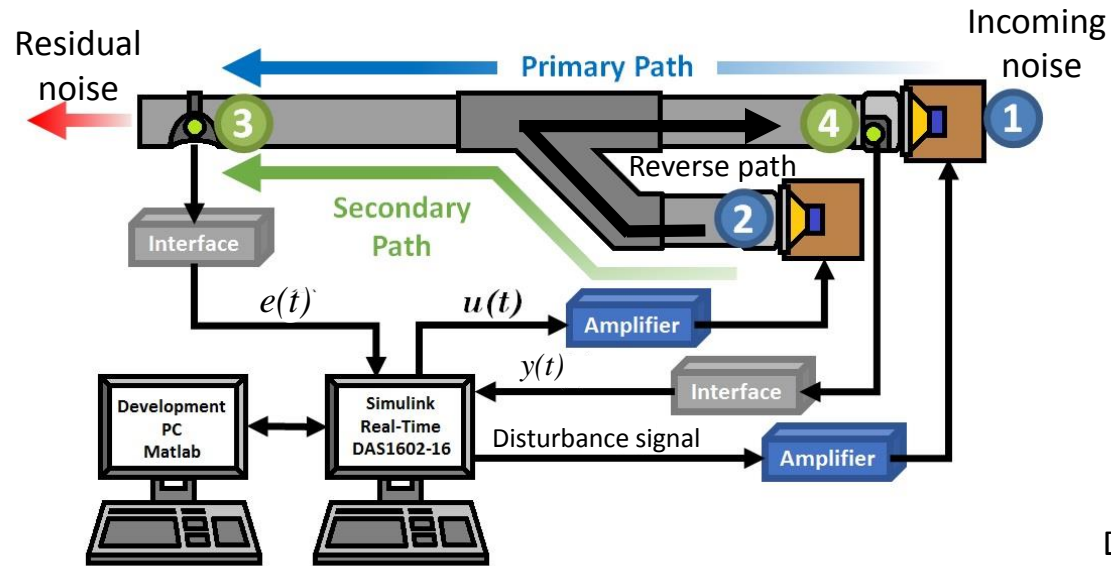
Adaptive Feedforward Noise Attenuation



Discrete-time T.F.

$$M = B_M / A_M ; G = B_G / A_G$$

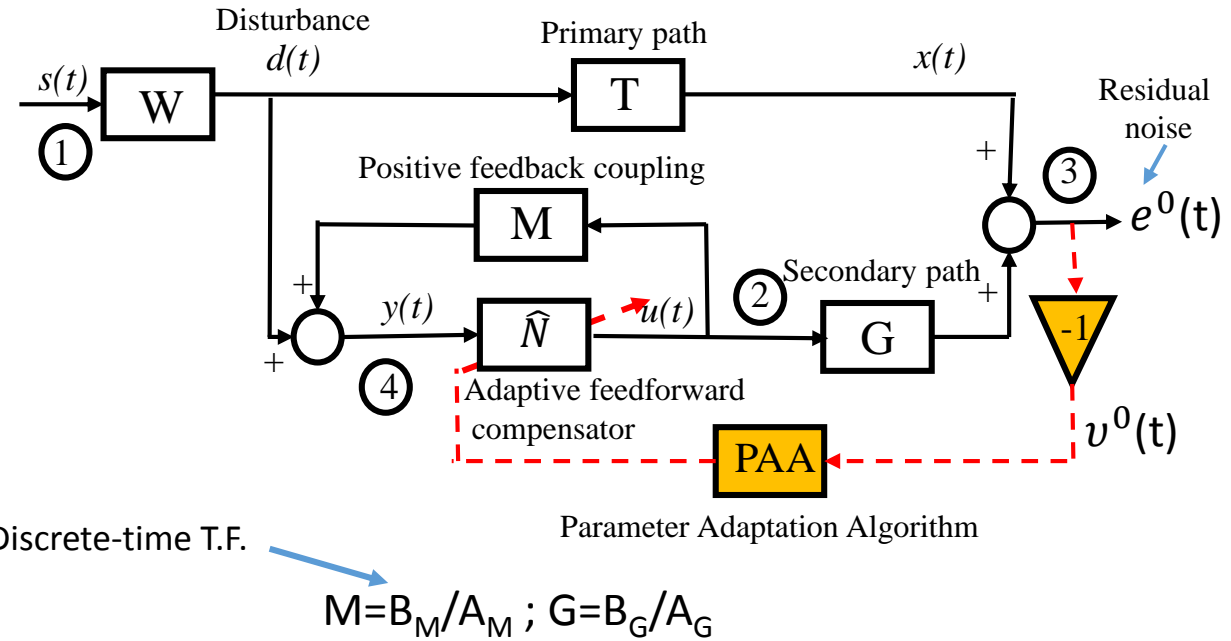
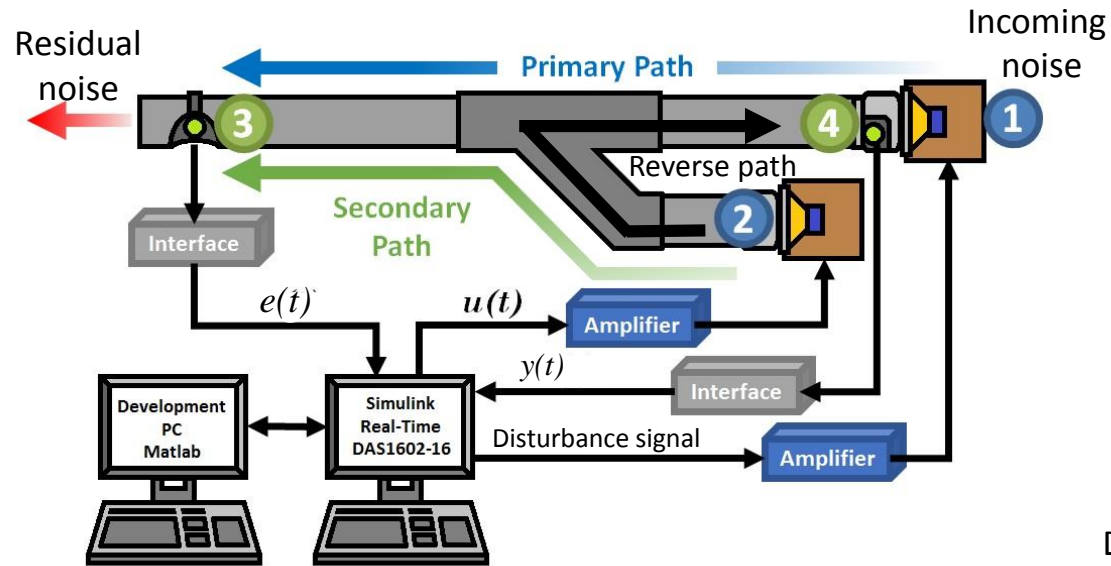
Adaptive Feedforward Noise Attenuation



State of the art (before 2011)

- Stability problems caused by the internal positive coupling
- Use of refined LMS (XLMS, FULMS...) adaptation algorithms but without a stability analysis

Adaptive Feedforward Noise Attenuation



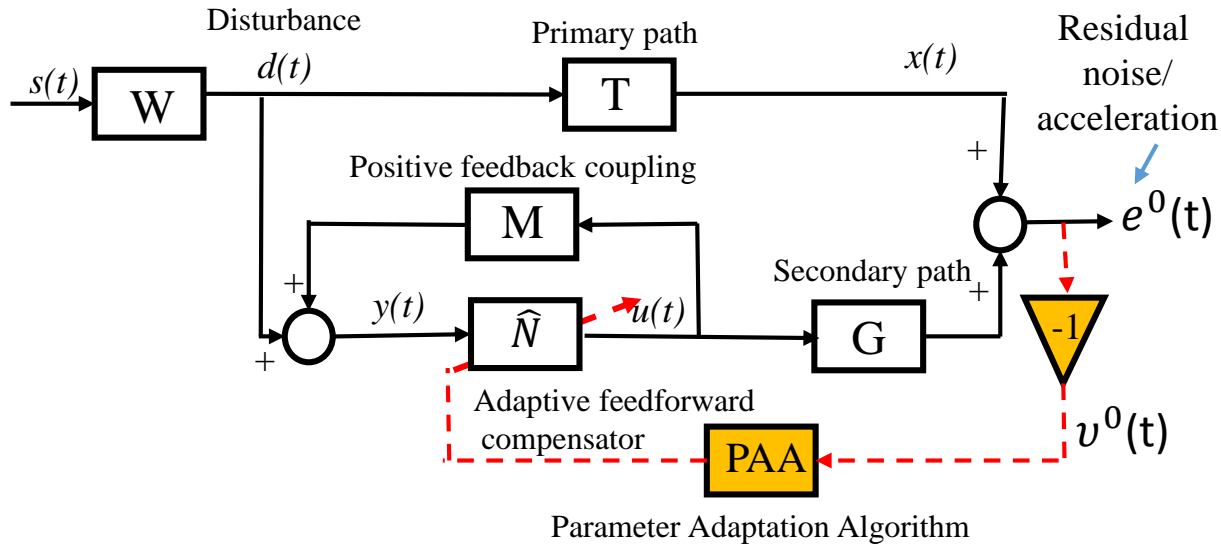
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New solutions

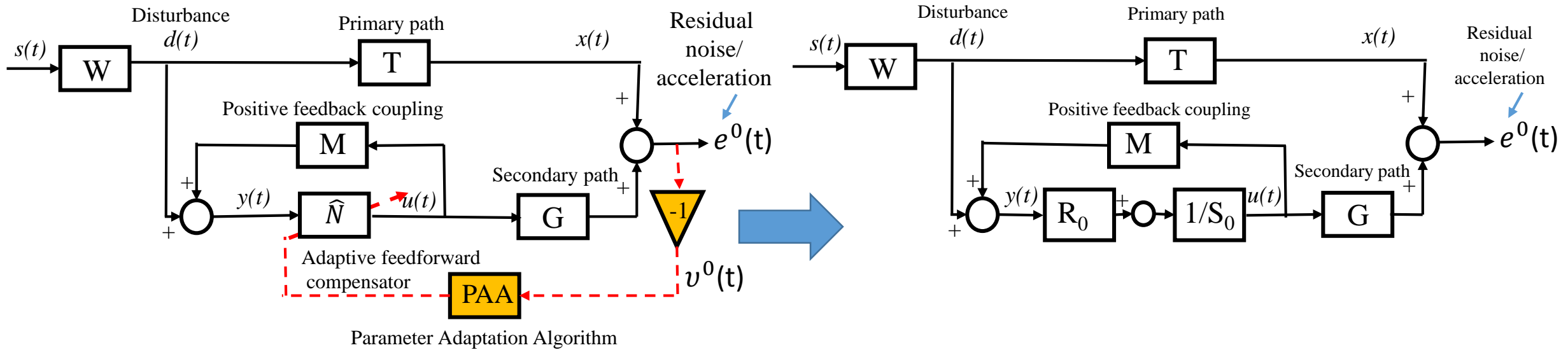
- Introduction of stability based adaptive algorithms
- Inherent stable structures despite internal positive feedback using Youla-Kucera parametrization

YK Parametrized Adaptive Feedforward Noise/Vibration Attenuation



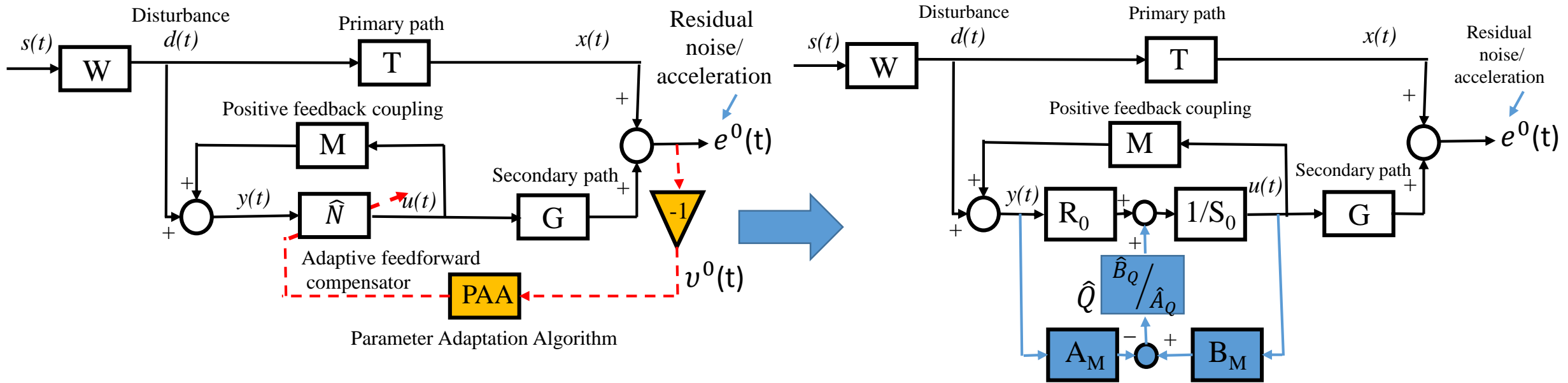
- **Problem:** To assure the stability of the internal coupling positive feedback loop independently of the parameters of the feedforward compensator which should minimize the residual noise

YK Parametrized Adaptive Feedforward Noise/Vibration Attenuation



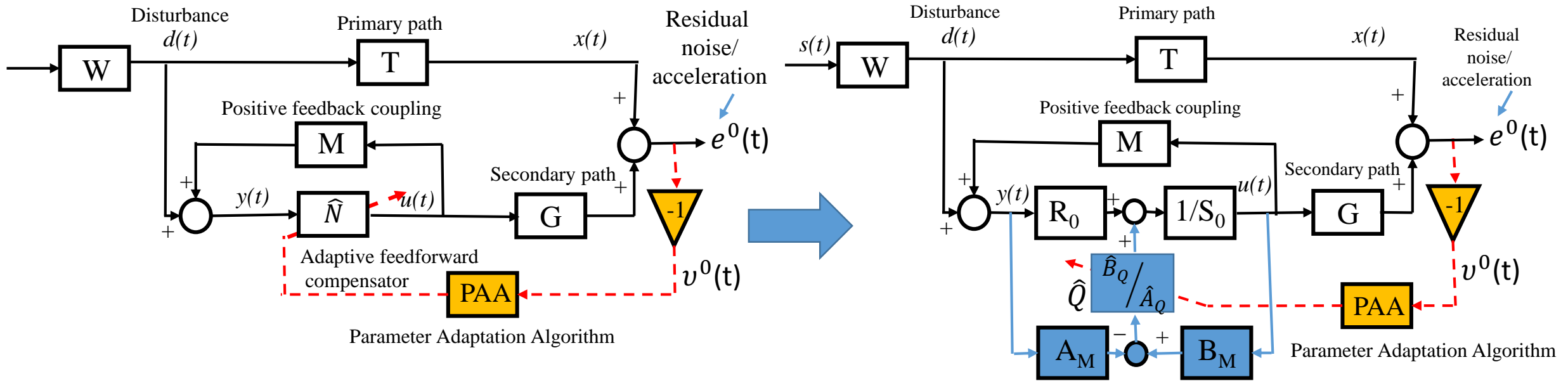
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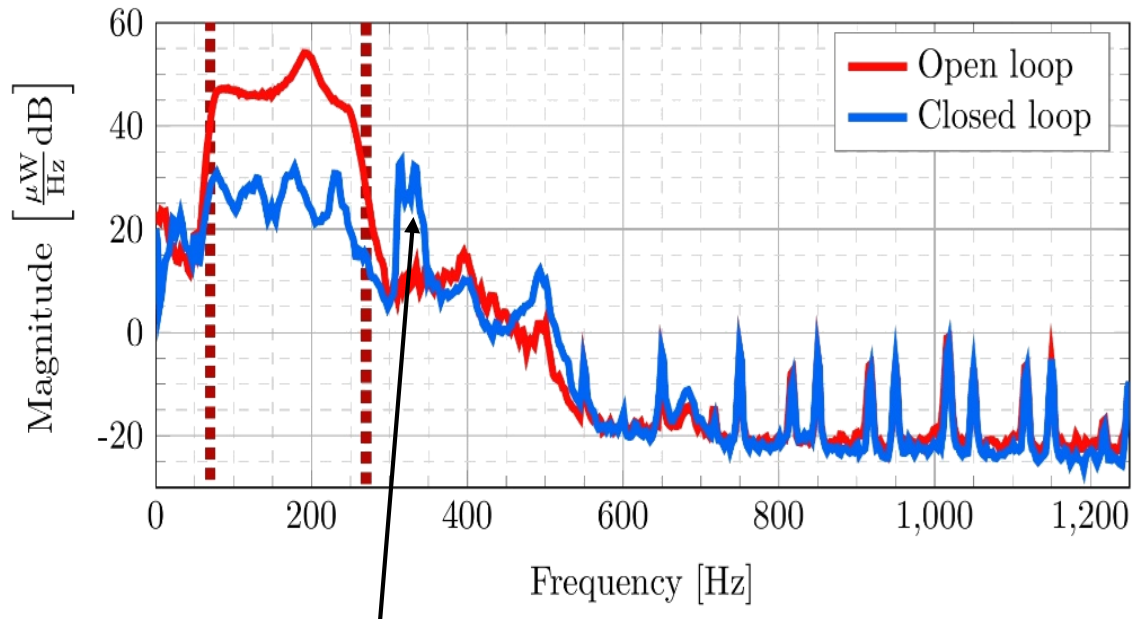


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Adaptive Feedforward Broad-band Noise Attenuation

Mainly dedicated to attenuation of broad-band disturbances

Stability based standard IIR compensator



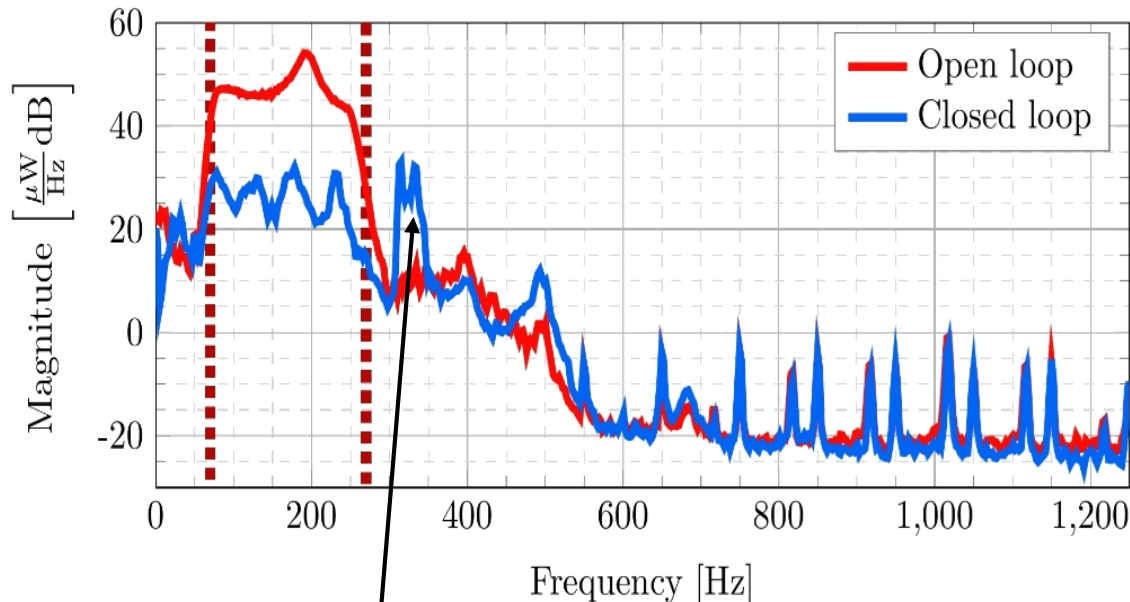
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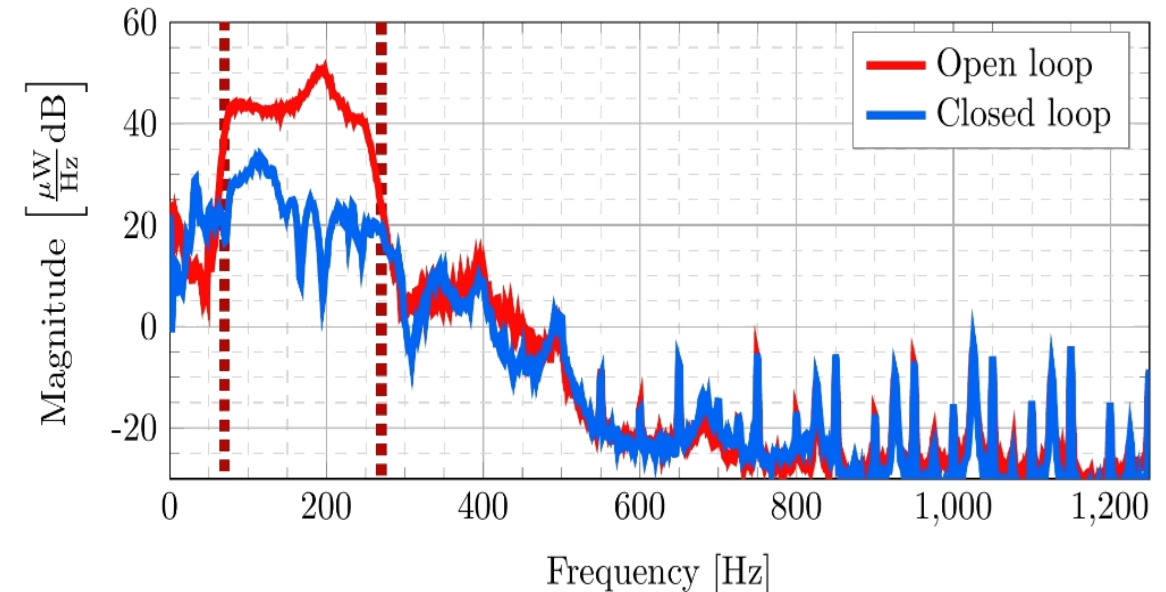
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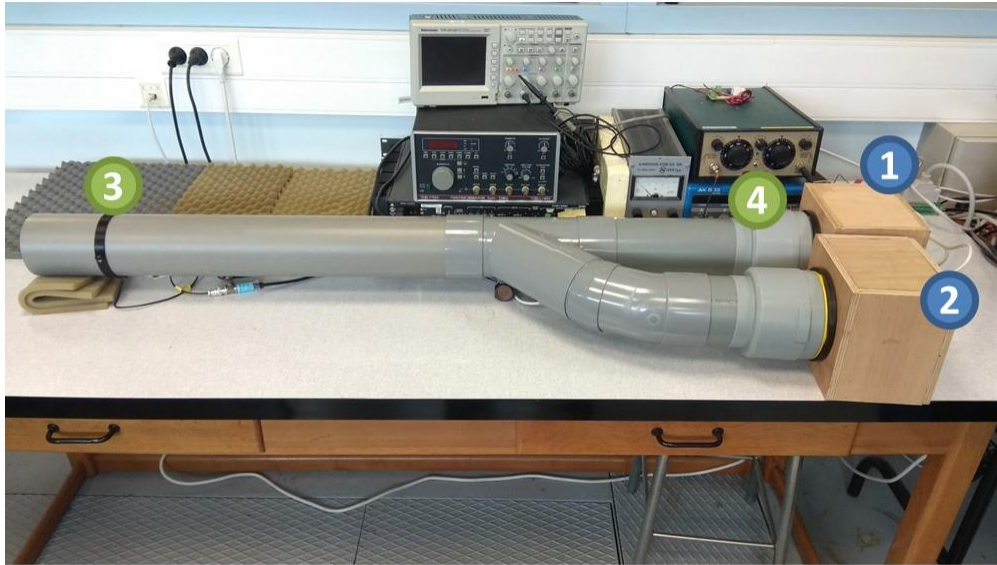
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Stability based YK – IIR compensator



The central controller forces some (IIR) or all (FIR) poles to be enough far from the unit circle

Beyond the delay barrier using YK parametrization

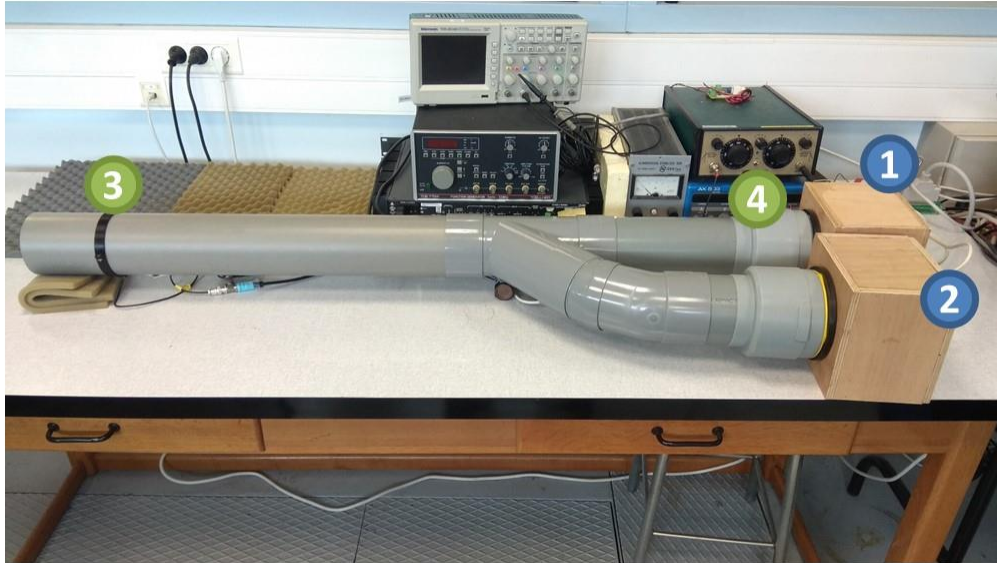


There are potential application areas where:

Length secondary path (2→3) > Length primary path (4→3)
(*delay*) (delay)

Beyond the theoretical limit for standard Feedforward Compensation (***Secondary path shorter than Primary path***)

Beyond the delay barrier using YK parametrization



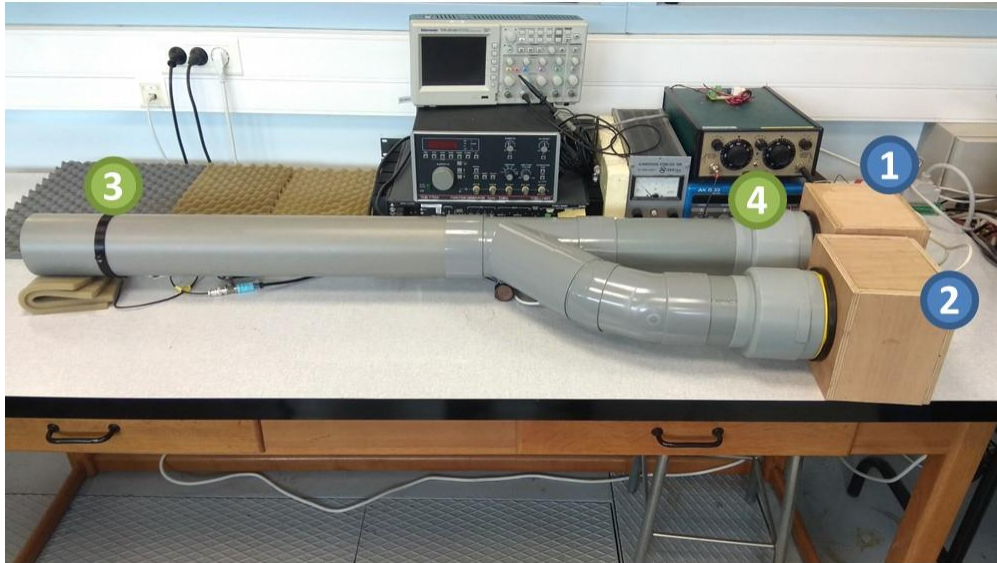
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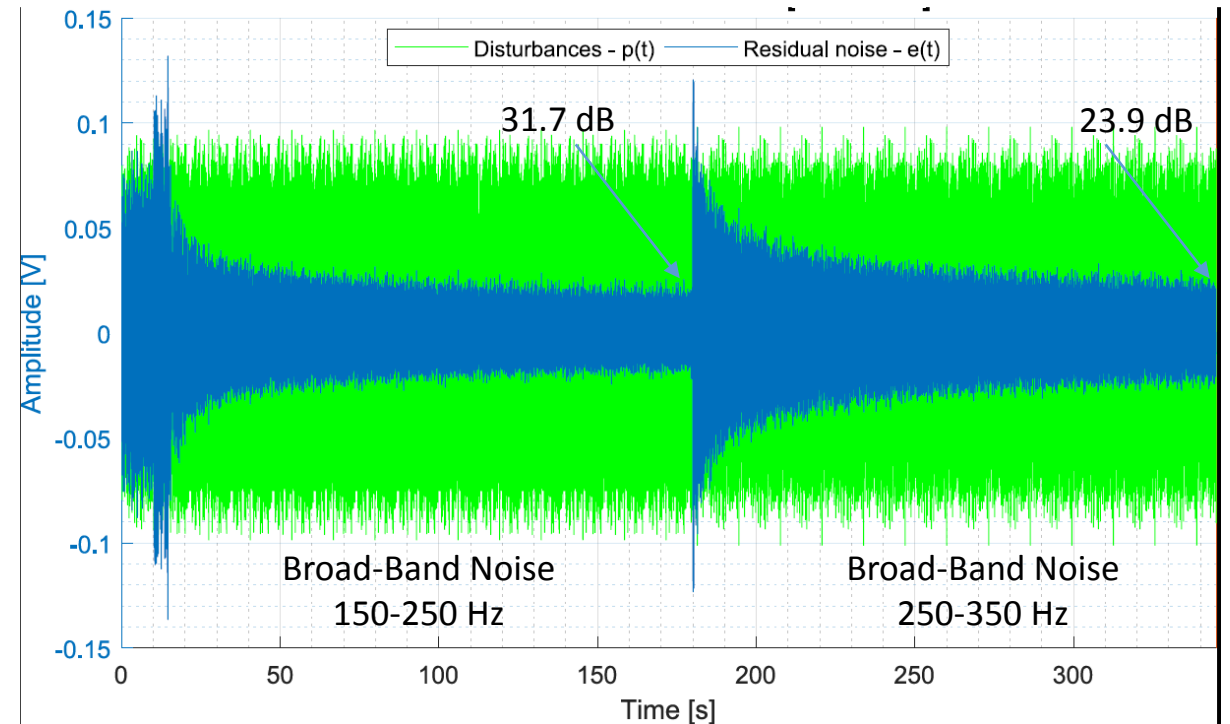
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Results using **FIR YK** adaptive feedforward compensator
(60 parameters)

Design of adaptive feedforward attenuation schemes

- Establish an equation for the residual error (noise/acceleration) of the form:

$$v(t + 1) = -e(t + 1) = H_v(q^{-1}) [\theta - \hat{\theta}]^T \phi(t) \quad \text{For } \hat{\theta} = \text{const.}$$

(not obvious at a first glance)

θ = vector of optimal parameters of the compensator filter (unknown)

$\hat{\theta}$ = vector of adjustable parameters of the compensator filter

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- Introduce a filter L on the data (will results from stability considerations) $\psi(t) = \phi_f(t) = L(q^{-1})\phi(t)$
- Re-write equation of the residual error as

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- Replace $\hat{\theta} = \text{const.}$ by a time varying one

$$\nearrow v(t + 1) = H(q^{-1}) [\theta - \hat{\theta}(t + 1)]^T \psi(t)$$

This is a standard form for the synthesis of stable adaptive schemes.

Stability based parameter adaptation algorithms

θ = vector of parameters ($\hat{\theta}(t)$ = estimated parameter vector)

ϕ = vector of measurements (observation vector)

ψ = regressor vector: $\psi = L\phi$; $L = \text{filter}$

- Adaptation error (*a priori*)
- Stability based adaptation algorithms
- Data Filter

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- Stability based adaptation algorithms
 - $\hat{\theta}(t+1) = \hat{\theta}(t) + \gamma \psi(t) \frac{v^0(t+1)}{1 + \gamma \psi^T(t) \psi(t)}$ Scalar constant adaptation gain (γ)
 - $\hat{\theta}(t+1) = \hat{\theta}(t) + F(t) \psi(t) \frac{v^0(t+1)}{1 + \psi^T(t) F(t) \psi(t)}$ Matrix adaptation gain (F)

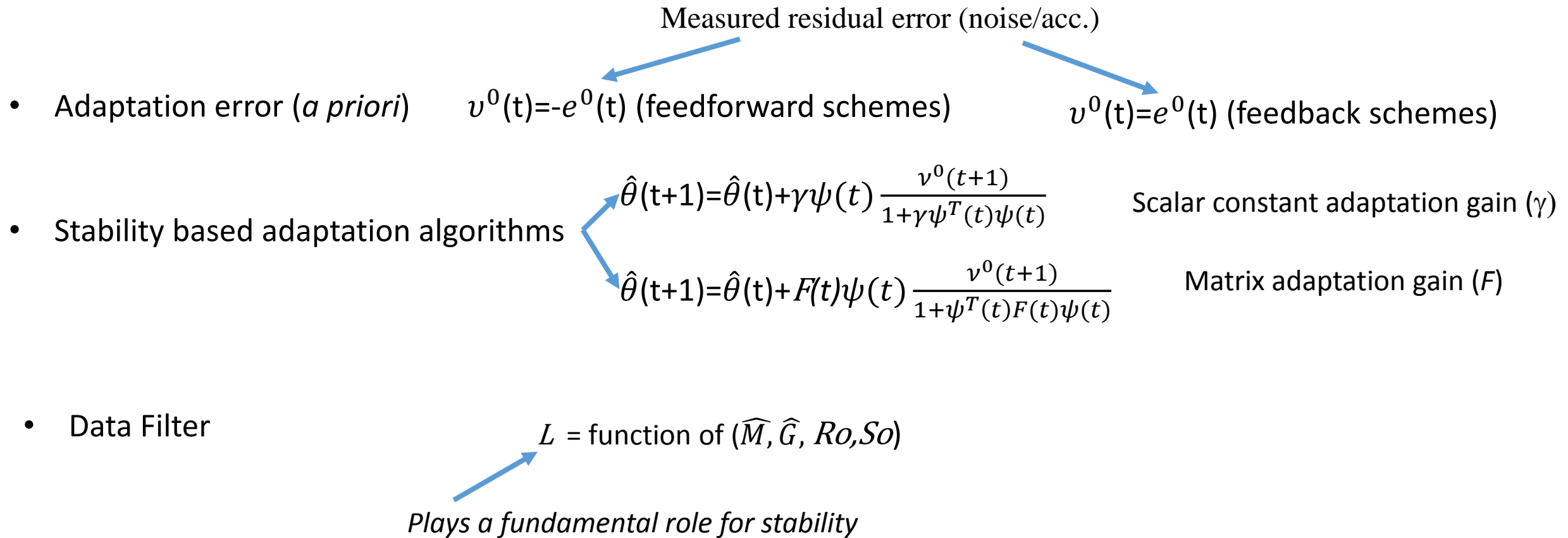
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Stability conditions for adaptive feedback/feedforward noise/vibration attenuation

$$v(t + 1) = H(q^{-1}) [\theta - \hat{\theta}(t + 1)]^T \psi(t)$$

Stability condition:

$H(z^{-1})$ (or $H(z^{-1}) - \lambda/2$ for time varying adaptation gain) **should be Strictly Positive Real (SPR) (*)**

$$H(q^{-1}) = H_v(q^{-1}) \cdot [L(q^{-1})]^{-1} \quad H_v(q^{-1}) = f(G, M, R_0, S_0)$$

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Best choice for L (trying to approach $H=1$): $L = f(\hat{G}, \hat{M}, R_0, S_0)$

When doing this, condition (*) becomes in most of the cases:

$\frac{\hat{G}}{G}$ and $\frac{\hat{M}}{M}$ should be **strictly positive real T.F.**

Stability conditions for adaptive feedback/feedforward noise/vibration attenuation

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Or equivalently:

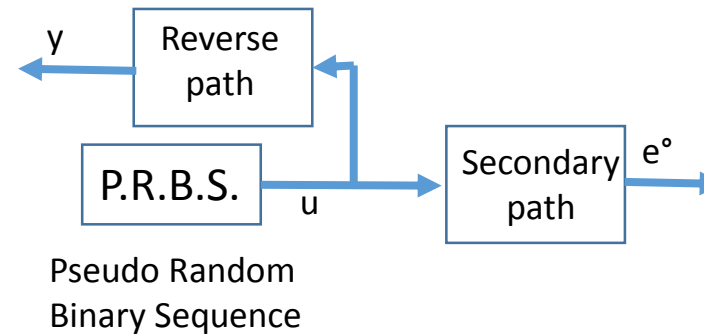
The phase difference between \hat{G} and G and between \hat{M} and M should be $< |90^\circ|$ at all frequencies (can be relaxed using averaging arguments)



Consequence: one needs good models of G and M !
(system identification is a must)

System identification – a key point for stability

Step 1 Data acquisition under experimental protocol (15 to 30s)



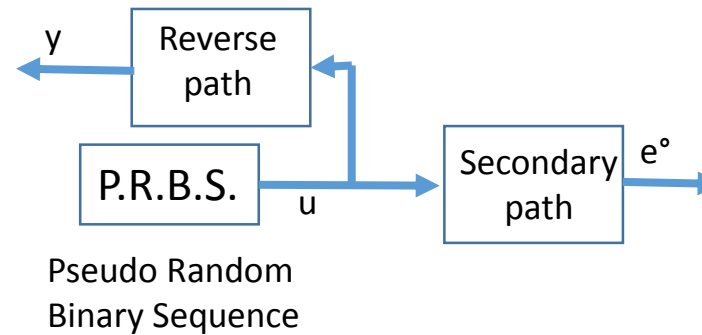
Step 2 > Estimation of the model order from data (Duong-Landau method)

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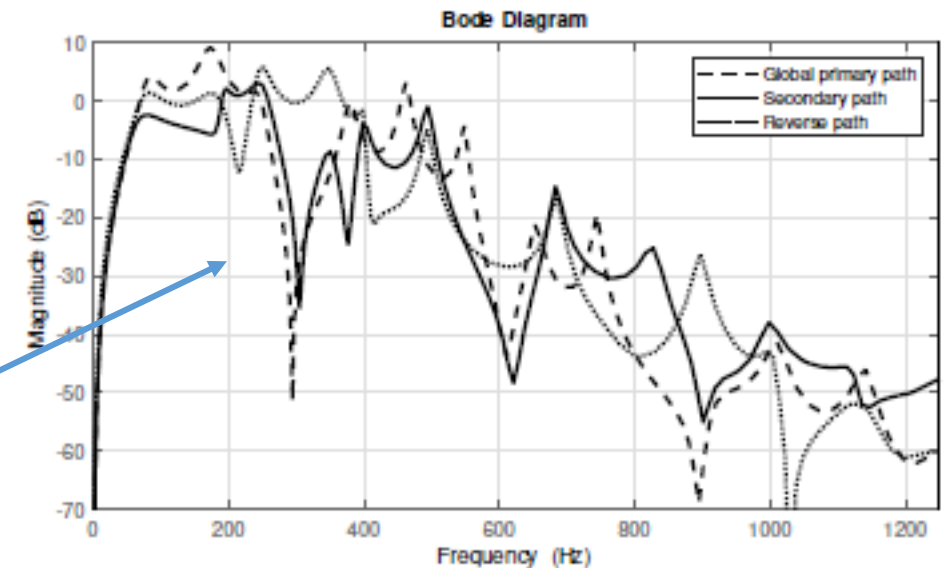


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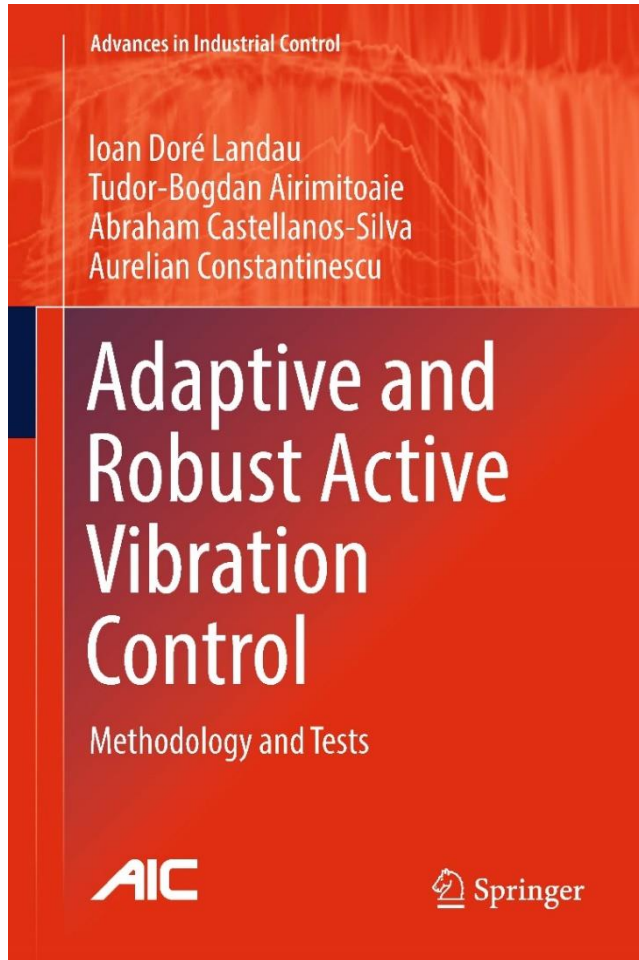
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- *High order models with many resonances and anti-resonances*
- *Double differentiator behaviour*



The methodology – A summary



- This methodology has been developed in the field of active vibration control and applied in the field of active noise control
- R. Melendez et al. « Data driven design of tonal noise feedback cancellers », IFAC World Congr. 2017, Toulouse
- I. Landau et al. « Robust and Adaptive Feedback Noise Attenuation in Ducts”, IEEE Trans. on CST, March 2019
- I. Landau et al. « Why one should use Youla Kucera parametrization in adaptive feedforward noise attenuation? » IEEE –CDC, Nice, 2019
- I. Landau et al. « Beyond the delay barrier in, active feedforward noise control using YK parametrization » J. of Sound and Vibr., Sept. 2019
- T. Airimitoiaie et al « Algorithms for adaptive feedforward noise attenuation—A unified approach and experimental evaluation », IEEE Trans. on CST, to be published

<http://www.gipsa-lab.grenoble-inp.fr/~ioandore.landau/adaptivecontrol/>

I.D. Landau & al « Adaptive YK parametrization for active noise and vibration attenuation »

Some research subjects

- Combined feedback and feedforward attenuation of noise /vibrations
- Adaptive feedback and feedforward attenuation of noise and vibration in the presence of significant changes in the models of the secondary and reverse paths

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*Preliminary results indicates the usefulness of Youla – Kucera parametrization.
However many problems remain to be solved!*

- T. Airimitoai I. Landau. « Combined adaptive feedback and feedforward compensation for active vibration control using Youla–Kucera parametrization”, J. of Sound and Vibr. , pp 422-441, 2018
- Ph. Mulhaupt et al. “Asymptotic rejection of nonvanishing disturbances despite plant–model mismatch » International J. of Adaptive Control and Signal Porcessing , 2012, pp1090 -1110
- B. Vau I. Landau, «Youla-Kucera feedback disturbance rejection in the presence of plant uncertainties” IEEE-CDC 2019, Nice, 2019

Thank you for your attention!

*Do not hesitate to contact me:
ioan-dore.landau@gipsa-lab.fr*