

QUADROTOR CONTROL USING ADAPTIVE ADRC

Adaptive Filtering



INTRODUCTION

In this work, the altitude control of a quadrotor unmanned aerial vehicle is treated using its altitude dynamics in hover mode.

Due to persistent aerodynamic disturbances, the control of a quadrotor unit is cumbersome; especially, the ground wake effect which comes into play during landing.

In this work, an Adaptive Active disturbance rejection control (AADRC) is proposed to compensate for undesirable effects resulting in smoother control.

The adaptation of the ADRC controller is governed by an LMS algorithm on the extended state observer (ESO).



QUADROTOR MODEL

The nominal altitude model of a quadrotor is given as:

$$\ddot{z} = \frac{U_z}{m} \cos(\phi) \cos(\theta) - g + D_z$$

z is the altitude from ground level, U_z is the control input, m is the mass of the quadrotor, ϕ is the roll angle from the roll subsystem, θ is the pitch angle from the pitch subsystem, D_z is the aerodynamic drag and g is the gravity constant.

$$\ddot{z} = \frac{U_1}{m \left(1 - \rho \left(\frac{r}{4z_r} \right)^2 \right)} \cos(\phi) \cos(\theta) - g + D_z$$

In state space form: Let $x_1 = z$ and $x_2 = \dot{z}$ with output $y = x_1$

$$\begin{aligned} \dot{x}_1 &= x_2 \\ \dot{x}_2 &= G \frac{U_1}{m} \cos(\phi) \cos(\theta) - g + D_z \end{aligned}$$



ADRC CONTROL

Active disturbance rejection control (*ADRC*) is a relatively new control technique that has gained attention of the control community.

The novel *ADRC* technique developed by Jingqing Han was first introduced to English literature in 2001.

ADRC control technique is based on a unique type of disturbance observer known as extended state observer (ESO).

State observers, also known as estimators, are crucial in the design of modern control systems.

They estimate the internal variables of a physical plant (sometimes immeasurable with sensors) using the plant's input and output data only.

An obvious need for observers arise in flux estimation of A.C. induction motors.



ADRC CONTROL

$$\ddot{x} = f(x_1, x_2, \omega(t), t) + bu$$

In state space form:

$$\dot{x}_1 = x_2$$

$$\dot{x}_2 = f(x_1, x_2, \omega(t), t) + bu$$

$$y = x_1$$

where $y \in \mathbb{R}$ is the plant output, measurable and to be controlled, $u \in \mathbb{R}$ is the input, and $f(x_1, x_2, \omega(t), t) = F(t)$ is a function of the plant's states: $x_i \in \mathbb{R}$, external disturbances ω , and time t . $F(t)$ is regarded to as the total disturbance and assumed to be differentiable. The goal is usually to make y track a desired signal or reference by manipulating u . Taking $F(t)$ as an additional state variable $x_3 = F(t)$ and denoting $\dot{F}(t) = \bar{G}(t)$, with $\bar{G}(t)$ unknown, the original plant in (5) is now described in extended or augmented form as



ADRC: PLANT + ESO

$$\dot{x}_1 = x_2$$

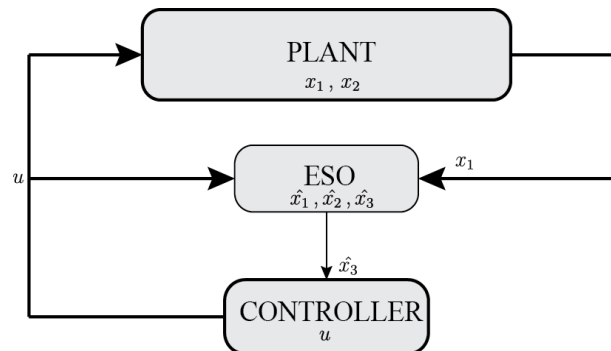
$$\dot{x}_2 = x_3 + bu$$

$$\dot{x}_3 = \bar{G}(t)$$

$$y = x_1$$

The system is now presented as:

$$u = \frac{u_0 - F(t)}{\hat{b}}$$



$$\dot{\hat{x}}_1 = \hat{x}_2 + \mathbf{p}_1(x_1 - \hat{x}_1)$$

$$\dot{\hat{x}}_2 = \hat{x}_3 + \mathbf{p}_2(x_1 - \hat{x}_1) + \hat{b}u$$

$$\dot{\hat{x}}_3 = \mathbf{p}_3(x_1 - \hat{x}_1)$$

$$f(x_1, x_2, \omega(t), t) - F(t) \approx 0.$$

$$\ddot{x} = (f(x_1, x_2, \omega(t), t) - F(t)) + u_0$$

$$\dot{x}_1 = x_2$$

$$\dot{x}_2 = u_0$$

$$\ddot{x} = u_0, y = x_1, \mathbf{x} = [x_1, x_2]^T$$

■ $u_0 = k_1(x_{1d} - x_1) + k_2(\dot{x}_{1d} - x_2)$

STATEMENT OF PROBLEM

- We have a system with Gains/Parameters/Weights that need to be chosen.
- The choice of these Gains affect the performance of the Quadrotor's states
- Apart from using static gains, dynamic gains can be utilized
- Dynamic gains result in an adaptive system that accommodates unknown and unwanted factors while maintaining robustness due to a preset policy (cost-function)
- The LMS algorithm is proposed



ASSUMPTIONS AS USUAL ...

- **Continuous-time system**
 - Thus; use continuous-time algorithms (CT-LMS)
- **Deterministic System**
 - Thus, ignore the 'expectation' ($E[*]$) operator
- **Cost function**
 - $e = x_1 - \widehat{x}_1$ results in complex integral functions
 - A smart choice: $e = \dot{x}_1 - \dot{\widehat{x}}_1$
 - $J = [e]^2$



FORMULATION OF THE LMS

Define the error:

$$e = \dot{x}_1 - \dot{\hat{x}}_1$$

$$e = (x_2) - (\hat{x}_2 + p_1(x_1 - \hat{x}_1))$$

Set Cost-function:

$$J = [e]^2$$

$$J = (x_2 - \hat{x}_2 - p_1 x_1 + p_1 \hat{x}_1)^2$$

Gradient of Cost-function: $\nabla_{p_1} J = 2(x_2 - \hat{x}_2 - p_1 x_1 + p_1 \hat{x}_1)(x_1 - \hat{x}_1)$

$$\nabla_{p_1} J = 2(x_2 - \hat{x}_2)(x_1 - \hat{x}_1) - 2p_1(x_1 + \hat{x}_1)(x_1 - \hat{x}_1)$$



LMS ADAPTATION

$$e = (x_2 - \hat{x}_2) - p_1(x_1 - \hat{x}_1)$$
$$\nabla_{p_1} J = 2(x_2 - \hat{x}_2 - p_1 x_1 + p_1 \hat{x}_1)(x_1 - \hat{x}_1)$$

$$\nabla_{p_1} J = 2e(x_1 - \hat{x}_1)$$

Continuous-time LMS Algorithm

$$\frac{dW(t)}{dt} = -\frac{\rho}{2} \nabla_w J$$

$$\frac{dp_1(t)}{dt} = -\rho e(x_1 - \hat{x}_1)$$

The optimum p_1 is obtained by evaluating $\nabla_{p_1} J = 0$

$$(x_2 - \hat{x}_2) - p_1(x_1 - \hat{x}_1) = 0$$

$$p_1 = \frac{(x_2 - \hat{x}_2)}{(x_1 - \hat{x}_1)}$$



CT-LMS ALGORITHM FOR ADAPTIVE ADRC

Final Algorithm

- Initialize ESO gain p_1 and adaptive gain ρ

$$p_1 > \epsilon \text{ and } \rho > 0$$

- Calculate the Error

$$e = (x_2 - \hat{x}_2) - p_1(x_1 - \hat{x}_1)$$

- Update the ESO gain

$$\dot{p}_1 = -\rho e(x_1 - \hat{x}_1)$$



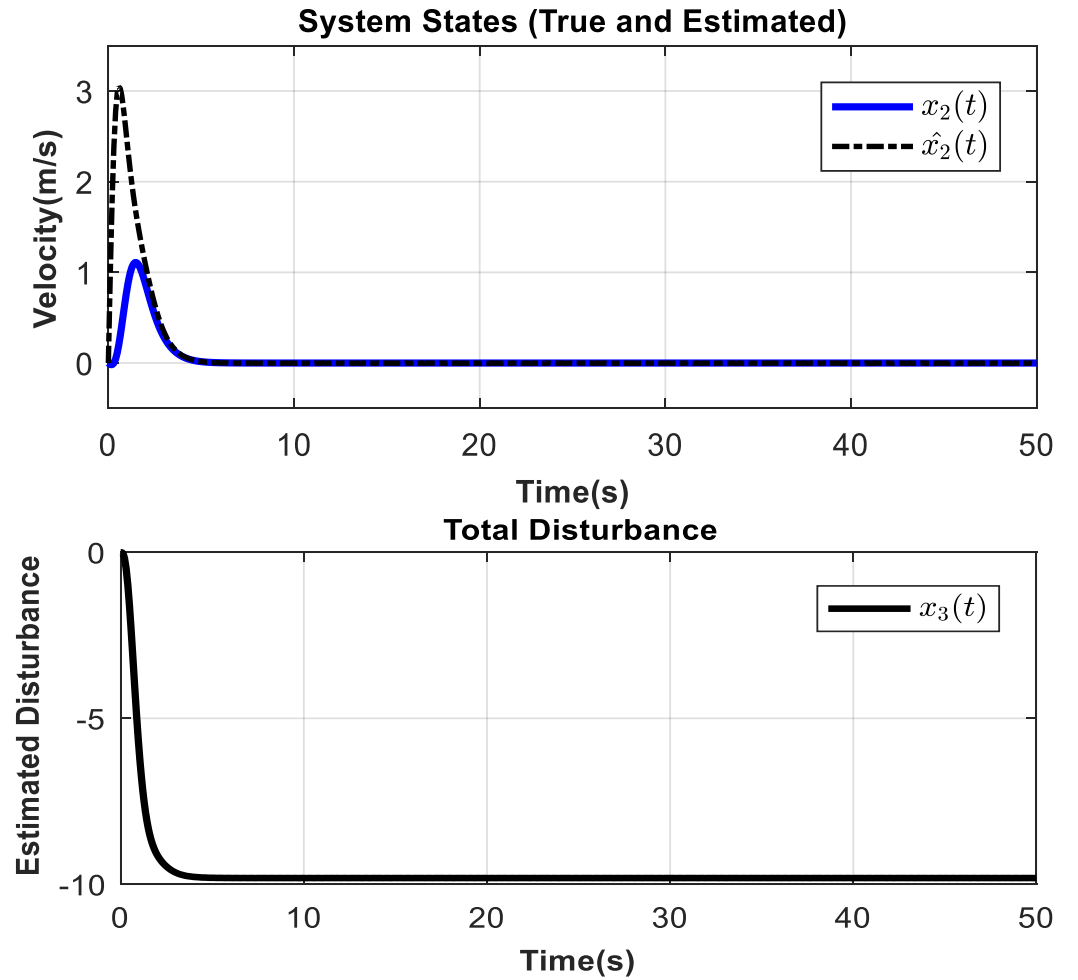
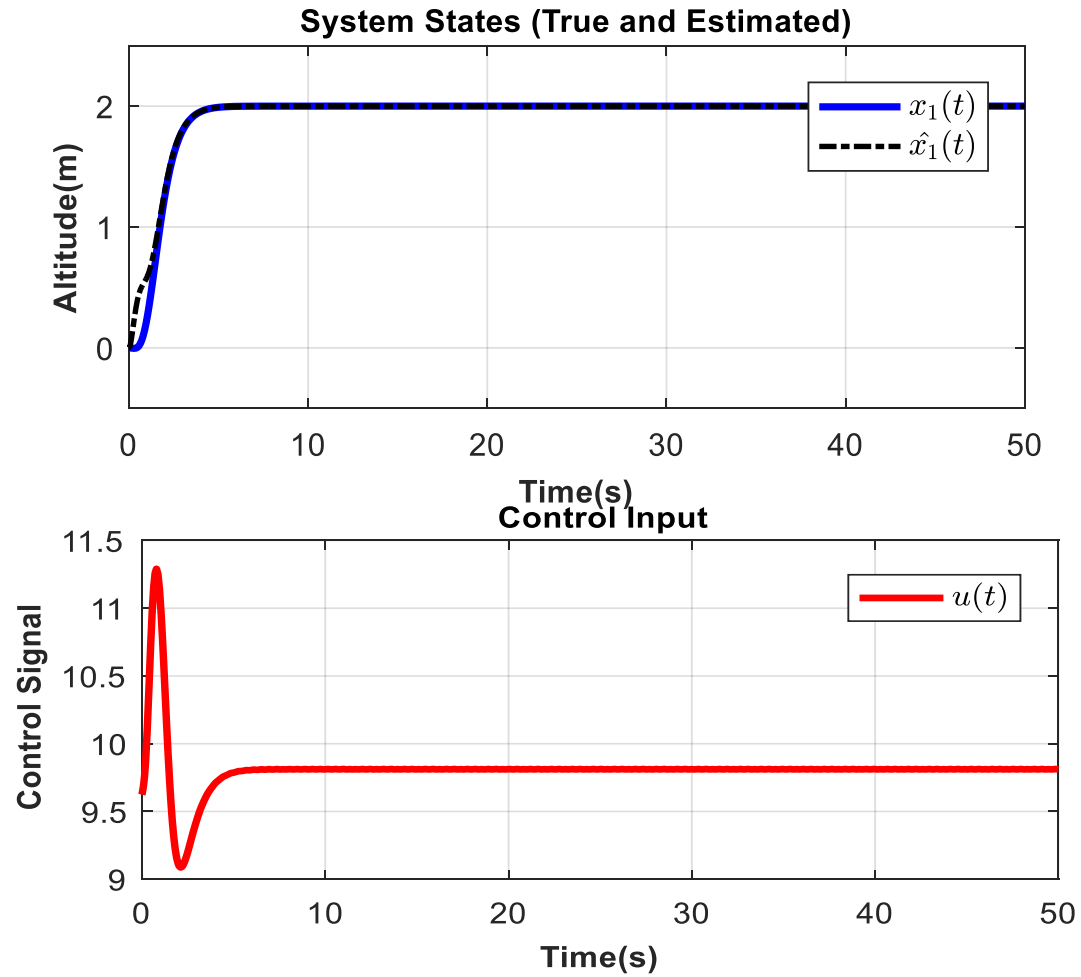
SIMULATION & PARAMETERS

> Matlab Simulation

No.	Quadrotor Parameters		
	Parameter	Symbol	Value
1	Mass	$m(kg)$	2
2	Rotor radius	$r(m)$	0.1905
5	Altitude sensor noise	$\sigma_z^2(m)$	0.14^2
3	Aerodynamic friction coefficient	k_z	0.3729
4	Ground effect coefficient	ρ	8.6
5	Gravitational constant	$g(ms^{-2})$	9.81
6	Initial p_1	p_1	50
7	Adaptive gain	ρ	1

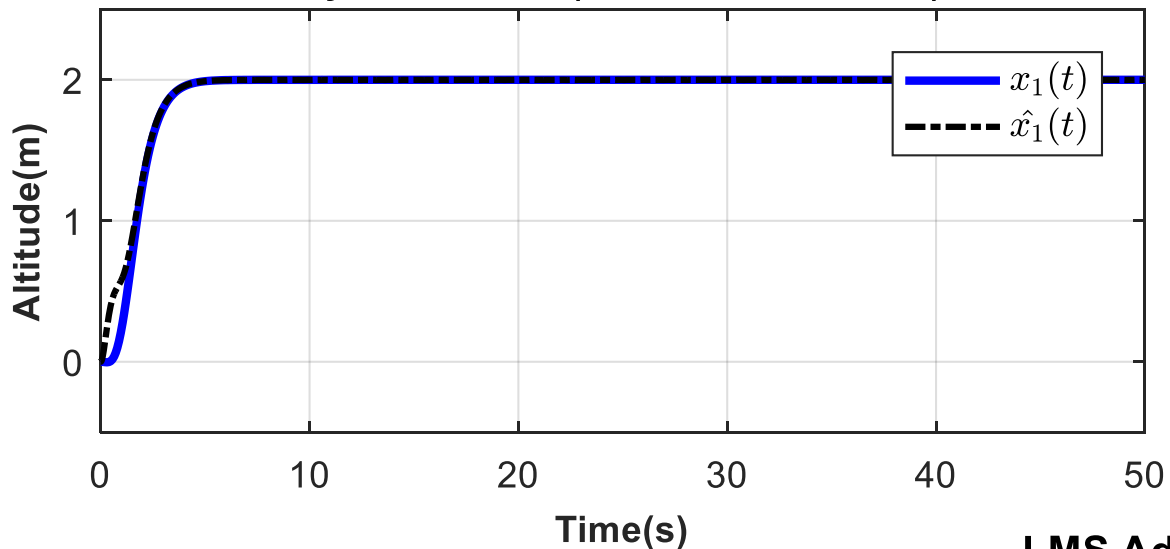


RESULTS

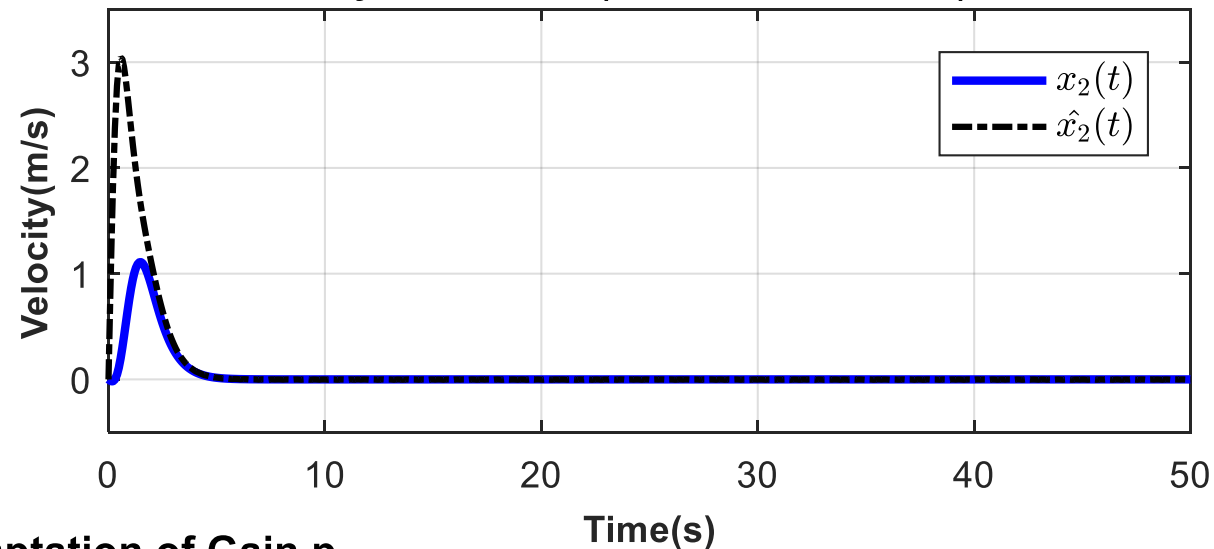


RESULTS

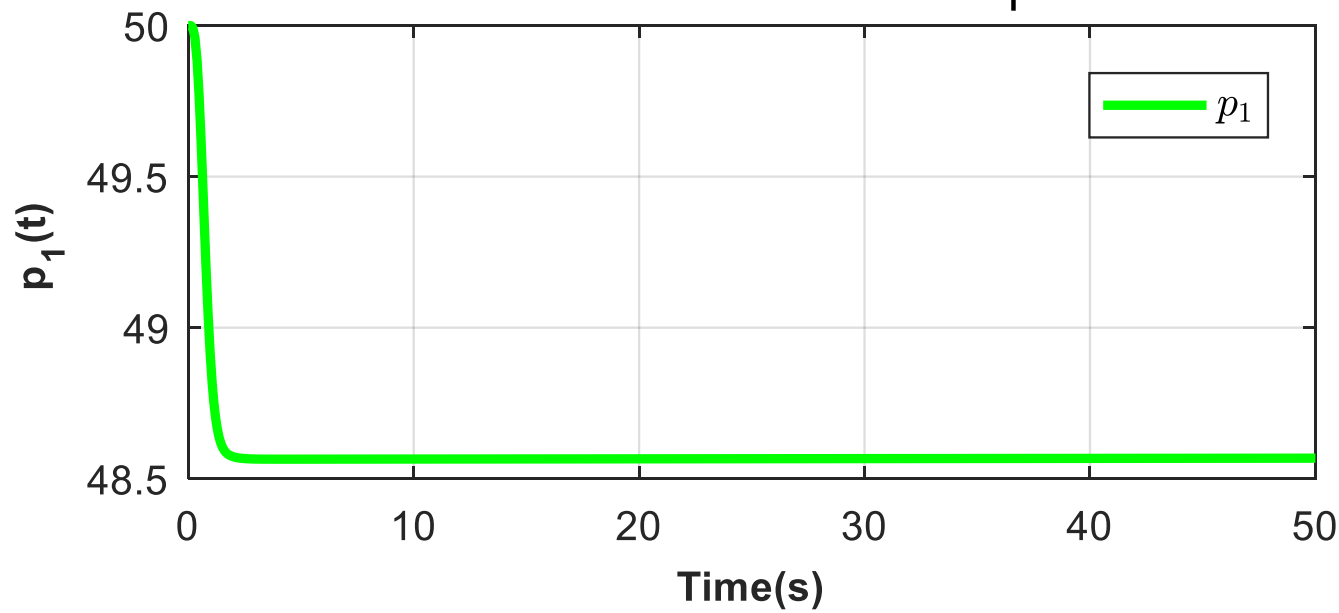
System States (True and Estimated)



System States (True and Estimated)



LMS Adaptation of Gain p_1



SUMMARY & CONCLUSION

- In summary, the quadrotor altitude control was solved using a technique which observes the total disturbances in the system and actively compensates for it.
- An LMS algorithm for the adaptation of the observer gain was presented and successfully implemented in Matlab.

Optimal weight p_1 via LMS = 48.4

Optimal weight p_1 via SQP = 55

- Results are pretty.
- Need for further analysis (stability, transients, multiobjective).



REFERENCES

- W. Zhou, S. Shao, and Z. Gao, "A Stability Study of the Active Disturbance Rejection Control Problem by a Singular Perturbation Approach," *Appl. Math. Sci.*, vol. 3, no. 10, pp. 491–508, 2009.
- R. Mandoski, "On Active Disturbance Rejection in Robotic Motion Control," Poznan University of Technology, 2016.
- P. M. W. Plant, L. Sun, D. Li, K. Hu, K. Y. Lee, and F. Pan, "On Tuning and Practical Implementation of Active Disturbance Rejection Controller : A Case Study from a Regenerative Heater in a 1000 MW Power Plant," *Ind. Eng. Chem. Res.*, vol. 55, 2016.
- W. Tan, F. Jiayi, and C. FU, "Linear Active Disturbance Rejection Controllers (LADRC) for Boiler-Turbine Units," in *Proceedings of the 32nd Chinese Control Conference, IEEE*, 2013, pp. 5339–5344.
- S. Malladi and N. Yadaiah, "Design and Analysis of Linear Active Disturbance Rejection Controller for AVR System," in *2015 International Conference on Industrial Instrumentation and Control (ICIC), IEEE*, 2015, pp. 771–776.
- Y. Wang, G. Ren, and J. Zhang, "Anti-WindUp schemes for Nonlinear Active Disturbance Rejection Control in Marine Steam Turbine," *J. Mar. Sci. Technol.*, vol. 24, no. 1, pp. 47–53, 2016.
- M. R. Mokhtari, A. C. Braham, and B. Cherki, "Extended State Observer based control for coaxial-rotor UAV," *ISA Trans.*, vol. 61, pp. 1–14, 2016.
- J. Han, "From PID to Active Disturbance Rejection Control," *IEEE Trans. Ind. Electron.*, vol. 56, no. 3, pp. 900–906, 2009.
- R. Mado and P. Herman, "Survey on methods of increasing the efficiency of extended state disturbance observers," *ISA Trans.*, vol. 56, pp. 18–27, 2015.
- O. Elshazly, Z. Zyada, A. Mohamed, and G. Muscato, "Optimized Control of Skid Steering Mobile Robot with Slip Conditions," in *IEEE International Conference on Advanced Intelligent Mechatronics (AIM)*, 2015, pp. 959–964.
- J. Cao and B. Cao, "Design of Fractional Order Controllers Based on Particle Swarm Optimization," in *1ST IEEE Conference on Industrial Electronics and Applications*, 2006, pp. 1–6.
- Mathworks, "Simulink Design Optimization," *Matlab Documentation*, 2015. [Online]. Available: https://www.mathworks.com/help/pdf_doc/slido/slido_ug.pdf.
- Shlomo Karni And Gengsheng Zeng, "The Analysis of the Continuous-Time LMS Algorithm" in *IEEE Transactions on Acoustics. Speech. and Signal Processing*, Vol. 37, No. 4, 1989
- Peter J. Voltz, Frank Kozin, "Almost-Sure Convergence of the Continuous-Time LMS Algorithm" in *IEEE Transactions on Signal Processing*, Vol. 40, No 2. 1992.

