Fibre Optic Nonlinear Technologies [FONTE]

- A European Industrial Doctorate [GA766115]

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Executive Summary

System identification is the field that studies techniques to build mathematical models of dynamic systems. It can be used when no previous information is available from the system or when there is a model, but some parameters are unknown. The latter can also be called parameter identification. This is a powerful tool to simulate and understand real complex devices.

The basic steps to build a model of a real system starts by collecting information (data) about it. Followed by choosing a structure that will represent the desired system. An error function is defined to measure the difference between the collected information and the estimative from the model. The difference between both systems is used to improve the model and approximate it from the real system as close as possible.

One of the most important step of building a model is the choice of the structure that will represent the system. This can be a hard limitation of the model. For example, trying to model a nonlinear system with a linear model. Over the years, many different approaches were developed in the literature for system identification [1, 2]. A possible classification between the varieties of possibilities in structure is dividing them by linear and nonlinear models.

In this report, it will be given a general idea in how to apply system identification for linear system using a finite impulse response (FIR) filter and for a nonlinear system using Volterra filter.

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LIST OF ACRONYMS

AiPT	Aston Institute Of Photonic Technologies
EC	European Commission
EID	European Industrial Doctorates
ESR	Early Stage Researcher
FONTE	Fibre Optic Nonlinear Technologies
FIR	Finite Impulse Response
MSE	Mean Square Error
LMS	Least Mean Square
WSS	Wide-sense Stationary

1 LINEAR SYSTEM IDENTIFICATION WITH FIR FILTER

Figure 1 shows a generic diagram for a FIR filter. The idea is multiplying different instants of the signal in time to adjust the output for a desired signal. Because this filter represents only zeros of a transfer function, the impulse response of it is finite duration, which gives the name of the filter.

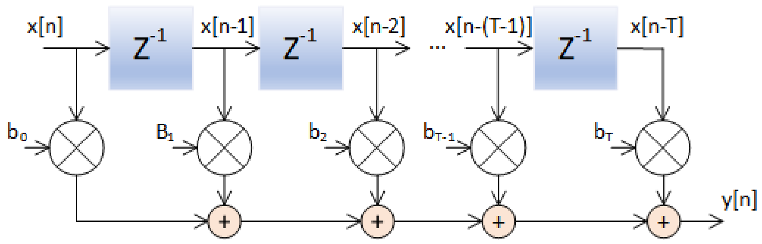

Figure 1 – FIR filter representation.

By fixing this structure to identify a system, we can only model systems with impulse response with finite duration. Figure 2 shows a diagram of a system identification process considering a FIR filter.

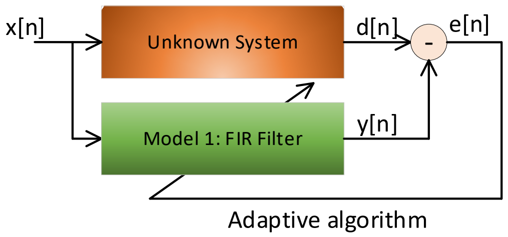

Figure 2 – System identification with FIR filter.

Considering the error as the difference between the output of the unknown system and the model, we define the loss function as the mean square error (MSE), as described by equation (1).

$$\mathcal{L} = E\{e[n]^2\} \tag{1}$$

where, $e[n] = y[n] - d[n]$.

The optimal weights (b_i) that minimize this loss function is the Winer solution. The Wiener solution has a premise that the signal is wide-sense stationary (WSS) and the autocorrelation and cross-correlation between the signal and the desired signal (from the unknown system) are known. Alternatively, we can use adaptive algorithms like least mean square (LMS) to estimate the gradient for each batch of data and update the weights in the direction to reduce the MSE.

After training the weights, it is possible to have a representation of the unknown system with a FIR filter. This might be used to understand the zeros location of the filter and the frequency response. In addition, it can offer as an alternative to use during simulations.

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2 NONLINEAR SYSTEM IDENTIFICATION WITH VOLTERRA FILTER

Using a linear system as described in the previous session might not reduce significantly the error between the unknown system and the FIR filter. Alternatively, changing the model to a nonlinear model, increases the search space in order to find a better approximation of the unknown system. Figure 3 shows an example of Volterra filter as a nonlinear model for system identification.

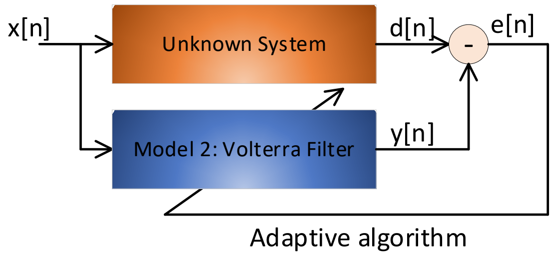

Figure 3 – System identification with Volterra filter.

Volterra filter is very similar to FIR filter. The key difference is that not only the output of Volterra filter has the weighted superposition of the delayed signals, but also has the weighted superposition of combinations of signal's exponentiations. Equation (2) describes the Volterra series.

$$y[n] = b_0 + \sum_{k_1} b_1[k_1] \cdot x[n-k_1] + \sum_{k_1}\sum_{k_1} b_2[k_1,k_2] \cdot x[n-k_1] \cdot x[n-k_2] + \sum_{k_1}\sum_{k_2}\sum_{k_3} b_3\,(k_1,k_2,k_3) \cdot x[n-k_1] \cdot x[n-k_2] \cdot x[n-k_3] + \cdots \quad (1)$$

where, $b_i(k_1, \dots, k_j)$ are the weights of the filter, called Volterra kernels.

By using the same loss function as define in equation (1), we can use LMS to update the Volterra kernels. Similar to section 1, after training, we have a nonlinear model of the unknown system which can be used to have a better comprehension of the system. Comparing the error between both models and the weights can also indicates if the system if better approximate for a linear or nonlinear model.

3 REFERENCES

[1] Åström, Karl Johan, and Peter Eykhoff. "System identification—a survey." Automatica 7.2 (1971): 123-162.

[2] Pintelon, Rik, and Johan Schoukens. System identification: a frequency domain approach. John Wiley & Sons, 2012.