PERFORMANCE OF A HIGH–PRECISION DIGITAL TUNING ALGORITHM[1]

†Chong–Gun Yu, †William G. Bliss and ‡Randall L. Geiger

†Department of Electrical Engineering
Texas A&M University
College Station, Texas 77843

‡Electrical and Computer Engineering
Iowa State University
Ames, Iowa 50011

Abstract

An iterative digital tuning algorithm which will be presented in [1] has been reviewed and simulated extensively, and its functionality has been investigated experimentally. This tuning algorithm is applicable to digitally programmable continuous–time filters. The algorithm estimates filter characterization parameters based upon a system identification method described in [2], and calculates control parameters for tuning adjustments. Extensive simulations show this algorithm converges to a solution within 10 iterations in most cases, even in the presence of various measurement errors, parameter variations and over–ordering effects. This algorithm is very insensitive to initial parameter variations, as good results are obtained even with 30% parameter error. This algorithm also attains good speed and accuracy in the presence of 5% measurement errors and high over–ordering effects. Experimental results with a second–order monolithic programmable OTA–C integrated circuit filter verify the robustness of the algorithm in tuning continuous–time filters.

1. Introduction

It has been considered that an iterative digital tuning algorithm offers improvements in speed and accuracy over other approaches using digital optimization techniques and conventional analog master–slave techniques [1]. Each iteration of the digital tuning consists of three phases: measurement, system identification and adjustment. Measurements are made by using a low speed analog to digital converter which converts signals grabbed by a high speed sample and hold circuit. To identify a deterministic linear time–invariant system in a robust way, an iterative complex least squares method [2] is used for the frequency–domain system identification. This identification method is robust in the presence of over–ordering effects and high measurement errors, so it makes the model–based tuning algorithm applicable to over–ordered systems.

The basic idea of this tuning algorithm is to estimate the model parameters of the OTAs (Operational Transconductance Amplifiers) of the digitally programmable continuous–time filter structure [3],[4] based on the reliable results of the system identification. Then the contol voltages and mirror gains of the OTAs are adjusted in such a way as to minimize the errors between the identified system and the desired system response. In this paper, we will focus on the performance of this tuning algorithm using the iterative complex least squares system identification method.

2. Digitally Programmable Continuous–Time Filter Architecture

The digitally programmable continuous–time filter architecture [3],[4] is shown in Fig. 1. This structure was selected specifically as a test vehicle for investigating the performance of the digital tuning algorithm. The structure of each biquadratic block is shown in Fig. 2. The ideal transfer function of the block is given by

$$\frac{V_{out}}{V_{in}} = \frac{(B_{hp})s^2 + (\frac{g_{m4}-g_{m3}B_{bp}}{C_7})s + (\frac{g_{m1}g_{m3}+g_{m2}g_{m3}B_{lp}}{C_6C_7})}{s^2 + (\frac{g_{m5}}{C_7})s + \frac{g_{m2}g_{m3}}{C_6C_7}} \quad (1)$$

where the B variables can be 0 or 1 depending upon the switch settings. Thus, the ideal transfer function of the system identification model for each biquad is given by

$$T(s) = \frac{s^2 + b_1 s + b_0}{s^2 + a_1 s + a_0} \quad (2)$$

which has only 4 degrees of freedom, instead of 5 in ordinary second order rational transfer functions. The coefficients are given respectively by

$$a_1 = \frac{g_{m5}}{C_7} \quad (3)$$

$$a_0 = \frac{g_{m2}g_{m3}}{C_6C_7} \quad (4)$$

$$b_1 = \frac{g_{m4} - g_{m3}B_{bp}}{C_7} \quad (5)$$

$$b_0 = \frac{g_{m1}g_{m3} + g_{m2}g_{m3}B_{lp}}{C_6C_7} \quad (6)$$

From (3)-(6), it follows that we can get independent or sequential adjustment of the system characterization parameters. This ideal model for the system is not exact because the actual physical system will have over-ordering problems due to the parasitic poles of the OTAs as well as other layout parasitics. However, the iterative complex least squares algorithm [2] makes it possible to use a low order model for identifying the higher order physical system. Thus, we can maintain near independence of adjustment of system characterization parameters even in the presence of significant parasitics.

3. Tuning Algorithm

In this section we briefly review the tuning algorithm, of which more details appear in [1]. The control mechanism relating the g_m of the OTAs to their control voltage V_c and current mirror gain M, is characterized by the linear equations.

$$g_{mi}(V_{ci}, M_i) = M_i K_i' \frac{W_i}{L_i}[V_{ci} - V_{ss} - V_{Ti}] \quad (7)$$

where K_i' and V_{Ti} are the process dependent transconductance and threshold voltage, M_i is the controllable output stage mirror gain, and W_i, and L_i are the width and length of the input differential pair devices. This can also be expressed as,

$$g_{mi}(V_{ci}, M_i) = M_i m_i(K_i', W_i, L_i)[V_{ci} + n_i(V_{Ti})] \quad (8)$$

We consider V_c and M as the control parameters for tuning the filters. V_c will be used for smaller (fine) adjustment while the mirror gain M will be used for more significant (coarse) adjustment.

The tuning algorithm based on the identification of the actual system consists of the following steps.

(1) Set the initial process parameters $m_i^{(0)}$ and $n_i^{(0)}$ of the biquads to their design (nominal) values.

(2) Obtain the transfer function coefficients ($a_1^{(0)}, a_0^{(0)}, b_1^{(0)}$, and $b_0^{(0)}$ of each biquad) of the system ID model from identification of the physical filter.

(3) Make an estimate of the system process parameters m_i and n_i for $i = 1,2,3,4,5$.

(4) Calculate the control voltages $V_{ci}^{(1)}$ and $M_i^{(1)}$ with the updated estimates for control parameters and adjust the transfer function coefficients to their design values.

(5) Obtain the coefficients ($a_1^{(1)}, a_0^{(1)}, b_1^{(1)}$, and $b_0^{(1)}$) from identification of the physical filter.

(6) Make improved estimates of the system process parameters m_i and n_i based upon the identifications at stage (2) and (5).

(7) Calculate the control voltages $V_{ci}^{(2)}$ and $M_i^{(2)}$ and adjust the transfer function coefficients.

(8) Repeat the step (5), (6), and (7) until a tuned state is obtained.

If the system model is ideal, this algorithm will converge after two iterations. In reality each OTA has parasitic poles and zeros, so actual

[1]This research was supported by the Texas Advanced Research Program.

91-645128/92$03.00 © 1992 IEEE

systems have higher order (over–ordered) transfer functions. Thus, more iterations are needed for convergence. The parasitic poles and zeros can be approximated by a single pole (ω_p) giving the following expression for the transconductance of each OTA:

$$g_m(s) = g_{mo}(\frac{1}{1 + s/\omega_p}) \tag{9}$$

then the transfer function of an actual biquad can be modelled for the tuning simulation by

$$T_{act}(s) = \frac{\tau^2 s^4 + 2\tau s^3 + (1 + \tau\frac{g_{m4}-g_{m3}}{C_7})s^2 + \frac{g_{m4}-g_{m3}}{C_7}s + \frac{g_{m1}g_{m3}}{C_6 C_7}}{\tau^2 s^4 + 2\tau s^3 + (1 + \tau\frac{g_{m5}}{C_7})s^2 + \frac{g_{m5}}{C_7}s + \frac{g_{m2}g_{m3}}{C_6 C_7}} \tag{10}$$

where $\tau = 1/\omega_p$, $B_{lp} = 0$, and $B_{hp} = B_{bp} = 1$. This over–ordering problem not only makes it hard to identify the system and thus hard to tune, but also leads to an undesirable phenomenon, so–called Q–enhancement.

For filters with medium to high Q the actual enhanced Q factor (Q^*) can be characterized by

$$Q^* \approx \frac{Q}{1 - 2\omega_o \tau Q} \tag{11}$$

where Q is the design value. If the parasitic pole exists at 10 times higher frequency than the resonant frequency, i.e. $\omega_o\tau = 0.1$, and the filter is designed with Q equal to or greater than 5, then the result is an oscillatory circuit. Therefore, predistortion techniques should be adapted to implement filters with high Q. At the initial implementation of a filter we use a predistorted value instead of the design value in order to prevent the filter from oscillation.

4. Simulation Results

In the tuning simulation, measurement errors (mn%), parameter variations (p%), and over–ordering factors (ω_o/ω_p) were included. The manufacturing process parameter variations were simulated via Monte Carlo techniques with random values of $\pm$p%. Frequency domain additive measurement errors of $\pm$mn% with uniform distribution were fed to the system identification algorithm. For every simulation, 50 measured noisy data obtained at 50 equally spaced frequency points were used for the system identification. The iterative complex least squares method was performed with the iteration limit set to 10. The iteration limit for tuning was also set to 10, and the filter is considered to be tuned if all the control voltages (fine adjustments) are within 9 bit accuracy with respect to the previous control voltages.

In order to evaluate the effect of various over–ordering problems on this tuning algorithm, a 6th–order elliptic lowpass filter was chosen for tuning which has a normalized cutoff frequency at 1 and 0.5 dB passband ripple. This filter consists of three second–order LowPass Notch (LPN) filters and its transfer function is given by

$$H_{elliptic}(s) = \prod_{i=1}^{3} \frac{s^2 + B_{0i}}{s^2 + A_{1i}s + A_{0i}} \tag{12}$$

The transfer function coefficients of the LPN filters and their quality factors and resonant frequencies are given in Table 1. Three LPN biquads were tuned separately to tune the 6th–order elliptic filter. The tuning results with various over–ordering factor, 1% measurement error and 5% parameter variation and various over–ordering factors are shown in Table 2, Fig. 3 and Fig. 4. For the third LPN filter, predistortion was performed for every over–ordering case because the filter has very high design Q of about 56, while for the first LPN filter no predistortion was performed due to its low Q. From the results it can be seen that this tuning algorithm converges fast and attains good results in the presence of over–ordering (up to $\omega_o/\omega_p = 0.1$) effects. But, the over–ordering factor $\omega_o/\omega_p = 0.2$ leads to a relatively big ripple error at the transition region. More iterations might give a better result.

To evaluate the effect of measurement errors and parameter variations on this tuning algorithm, a simple second–order lowpass filter was chosen with the following transfer function:

$$H_{LP}(s) = \frac{1}{s^2 + s + 1} \tag{13}$$

Tuning results with various parameter variations, 1% measurement error and over–ordering factor $\omega_o/\omega_p = 0.1$ are shown in Table 3, and Fig. 5. Even when 30% parameter variations were considered the tuned filter had a maximum gain (A_{max}) within 0.35% of the desired maximum gain and a resonant frequency within 0.01% of the desired frequency. Therefore it can be seen that this algorithm is not sensitive to the effect of parameter variations.

Tuning results with various measurement errors, 5% parameter variation and over–ordering factor $\omega_o/\omega_p = 0.1$ are shown in Table 4 and Fig. 6. Even in the presence of high measurement errors (up to 5%), this tuning algorithm attained good accuracy and fast convergence. However, 10% measurement error resulted in a poor tuned state. Actually, in this case, the tuning algorithm had not converged but was stopped by the iteration limit of ten. Actually, in this case, the iteration limit was exceeded. This phenomenon is caused by the fact that this model–based tuning algorithm heavily depends on the results of the system identification and the accuracy of the system identification is a function of the accuracy of measurements.

5. Experimental Results

This tuning algorithm was applied to tune several sample filters. The desired linear transfer functions were implemented with the digitally programmable monolithic continuous–time filter [3] which has only 6 bit resolution for the fine control. A workstation HP 9000/300 is used as the tuning host, and all instruments are connected on the HP–IB and are controlled by the tuning host. Measurements are made by the HP 54111D digitizing oscilloscope, which has programmable built-in commands for automatic measurements and has 6 bit single–shot accuracy and 8 bit accuracy with averaging. Excitation signals are generated from a HP 3325A programmable function generator.

First, the simple 2nd–order lowpass filter which has a resonant frequency of 500 KHz was implemented and tuned. Gain and phase data were measured at 50 equally spaced frequency points from dc to 600 KHz for each iteration and used for system identification. Fig. 7 shows that the tuned filter has a frequency response close to the desired one while the initially implemented filter has an erroneous frequency response. The entire tuning process took 9 iterations. Another tuning experimental result is shown in Fig. 8. The filter was tuned to a 2nd–order desired bandpass filter which has a resonant frequency of 100 KHz, a Q of 10 and a maximum gain of 1. After 7 iterations, the tuned filter had a resonant frequency of 99.7 KHz, a Q of 9.97 and a maximum gain of 0.995. These data were calculated from the identified transfer function.

6. Conclusion

In this paper, the performance of the iterative tuning algorithm to be presented in [1] for digitally programmable monolithic continuous–time filters has been analyzed and simulated extensively. Simulation results have showed that the algorithm is insensitive to the parameter variations and measurement noise unless the measured data are badly contaminated. This algorithm also attains good speed and accuracy in the presence of high over–ordering effects. The experimental results have demonstrated that the tuning algorithm can be successfully applied to tune filters with high accuracy.

References

1. C. G. Yu, W. G. Bliss and R. L. Geiger, "A Tuning Algorithm for Digitally Programmable Continuous-Time Filters," to be submitted to ISCAS '91.

2. C. G. Yu, W. G. Bliss and R. L. Geiger, "A Frequency Domain Parametric System Identification Algorithm for Continuous-Time Linear Filters," to be submitted to ISCAS '91.

3. K. H. Loh, D. L. Hiser, W. J. Adams and R. L. Geiger, "A Robust Digitally Programmable and Reconfigurable Monolithic Filter Structure," *IEEE International Symposium on Circuits and Systems*, Vol. 1, pp. 110-113, May 1989.

4. D. L. Hiser, "A Programmable Digitally Tuned CMOS OTA-C 2nd-Order Bandpass Filter Architecture," *Ph.D. Dissertation*, Texas A&M University, August 1990.

i	A_{1i}	A_{0i}	B_{0i}	ω_o	Q_p
1	0.933855	0.611899	4.36790	0.7822	0.8376
2	0.156221	0.934830	1.19243	0.9669	6.1891
3	0.017576	0.990620	1.02486	0.9952	56.628

Table 1 Coefficients of the low-pass notch filter models and their resonant frequencies and quality factors

	LPN1	LPN2	LPN3	6th-order Elliptic Filter	
ω_o/ω_p	No. of iteration	No. of iteration	No. of iteration	Passband ripple (dB)	3dB band error (%)
0.01	2	2	2*	0.501	0.30
0.05	5	6	4*	0.634	0.34
0.1	6	4*	4*	0.556	0.32
0.2	7	7*	5*	1.357	0.60

* Predistortion was performed

Table 2 Tuning results of the low-pass notch filters, thus the 6th-order lowpass elliptic filter with ω_o/ω_p over-ordering factors ($mn = 1.0\%$, $p = 5.0\%$)

Parameter Variations (p)	No. of Iteration	DC Gain A_0 (%)	Max. Gain A_{max} (%)	ω_{max} (%)	ω_o (%)
1%	7	0.005	0.27	0.13	0.10
5%	9	0.002	0.79	0.44	0.80
10%	4	0.232	0.32	0.02	0.60
20%	4	0.096	0.10	0.27	0.10
30%	6	0.937	0.35	0.72	0.01

Table 3 Tuning results of a simple lowpass filter with $p\%$ parameter variations ($mn = 1.0\%$, $\omega_o/\omega_p = 0.1$)

Measurement Error (mn)	No. of Iteration	DC Gain A_0 (%)	Max. Gain A_{max} (%)	ω_{max} (%)	ω_o (%)
0.1%	7	0.186	0.31	0.30	0.4
1%	9	0.002	0.79	0.44	0.8
5%	7	0.331	1.18	0.30	0.4
10%	10*	0.349	5.29	1.68	0.8

* Iteration limit was exceeded

Table 4 Tuning results of a simple lowpass filter with $mn\%$ measurement errors ($p = 5.0\%$, $\omega_o/\omega_p = 0.1$)

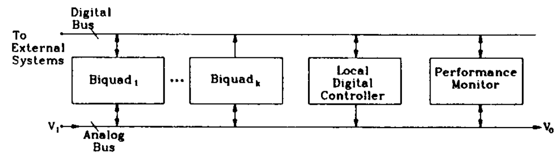

Fig. 1 Digitally Programmable Analog Filter Architecture[3]

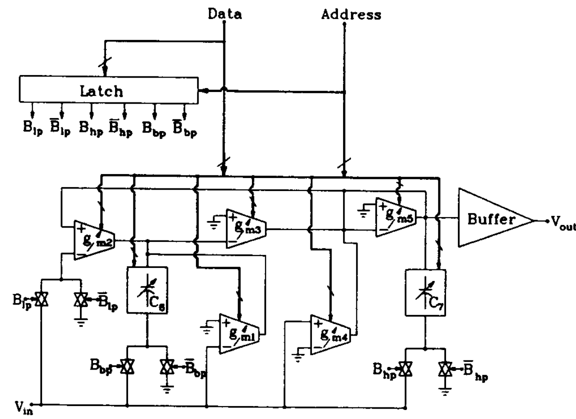

Fig. 2 Biquadratic Building Block[3]

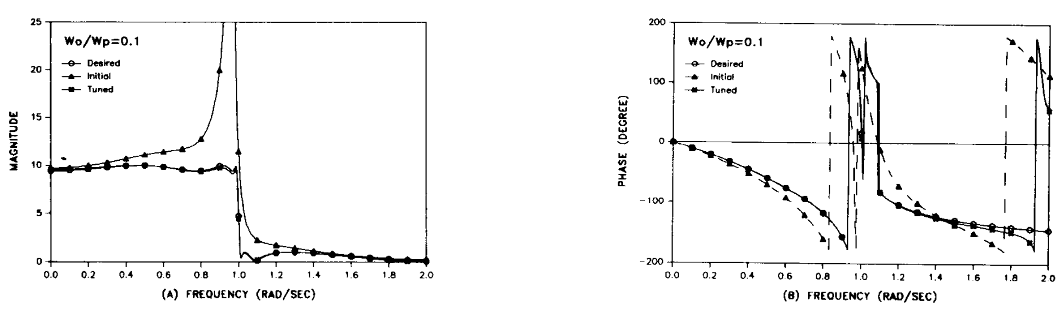

Fig. 3 Tuning results of the 6th-order elliptic lowpass filter (a) Magnitude response (b) Phase response (Over-ordering factor $\omega_o/\omega_p = 0.1$, Measurement errors mn=1%, and Parameter variations p=5%)

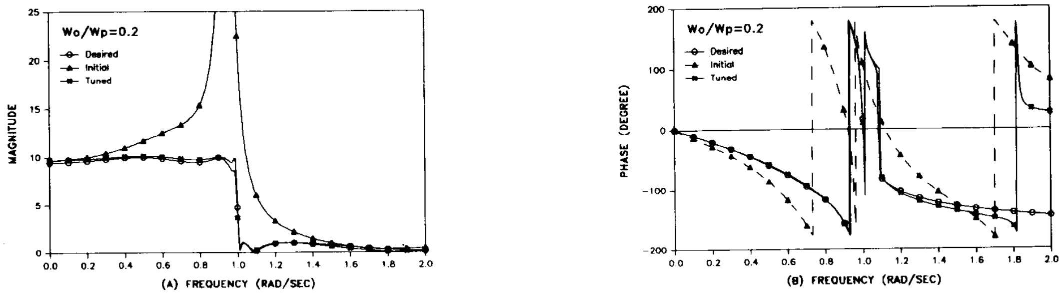

Fig. 4 Tuning results of the 6th-order elliptic lowpass filter (a) Magnitude response (b) Phase response (Over–ordering factor $\omega_o/\omega_p = 0.2$, Measurement errors mn=1%, and Parameter variations p=5%)

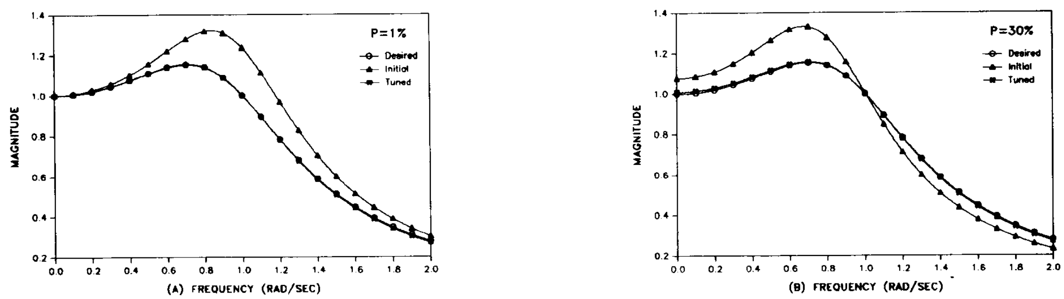

Fig. 5 Tuning results of the simple second-order lowpass filter (a) Parameter variations p=1% (b) Parameter variations p=30% (Over–ordering factor $\omega_o/\omega_p = 0.1$, and Measurement errors mn=1%)

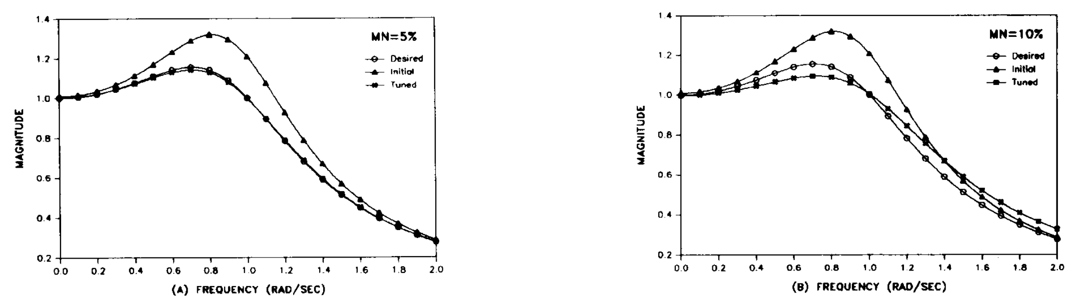

Fig. 6 Tuning results of the simple second-order lowpass filter (a) Measurement errors mn=5% (b) Measurement errors mn=10% (Over–ordering factor $\omega_o/\omega_p = 0.1$, and Parameter variations p=5%)

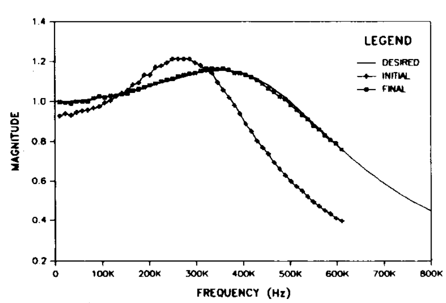

Fig. 7 Experimental tuning result of a simple second–order lowpass filter: magnitude response measured from the HP 54111D

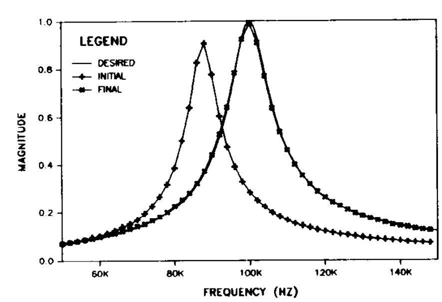

Fig. 8 Experimental tuning result of a second–order bandpass filter(Q=10): magnitude response measured from the HP 54111D