## THE HUBER CONCEPT IN DEVICE MODELING, CIRCUIT DIAGNOSIS AND DESIGN CENTERING

J.W. Bandler, S.H. Chen, R.M. Biernacki and K. Madsen

OSA-94-OS-15-V

May 17, 1994

<sup>©</sup> Optimization Systems Associates Inc. 1994

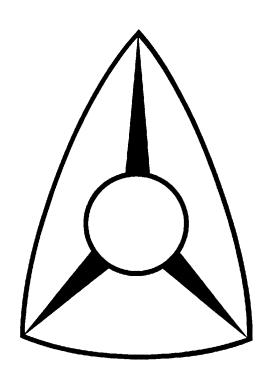
# THE HUBER CONCEPT IN DEVICE MODELING, CIRCUIT DIAGNOSIS AND DESIGN CENTERING

J.W. Bandler, S.H. Chen, R.M. Biernacki

Optimization Systems Associates Inc. P.O. Box 8083, Dundas, Ontario Canada L9H 5E7

K. Madsen

Institute of Mathematical Modelling The Technical University of Denmark DK-2800 Lyngby, Denmark





#### Introduction

circuit optimization must take into account model/measurement/statistical errors, variations and uncertainties

least-squares  $(\ell_2)$  solutions are notoriously susceptible to the influence of gross errors: just a few "wild" data points can alter the results significantly

the  $\ell_1$  method is robust against gross errors; however, it inappropriately treats small variations in the data

neither the  $\ell_1$  nor  $\ell_2$  alone is capable of providing solutions which are robust against large errors *and* flexible w.r.t. small variations in the data

the Huber solution can provide a smooth model from data which contains many small variations and such a model is also robust against gross errors

implemented in the CAD system OSA90/hope which was used to produce the examples in this presentation



#### The Huber Function

$$\rho_k(f) = \begin{cases} f^2/2 & \text{if } |f| \le k \\ k|f| - k^2/2 & \text{if } |f| > k \end{cases}$$

f represents an error function

k>0 is a threshold separating "large" and "small" errors the definition of  $\rho_k$  ensures a smooth transition at k

#### The Huber Norm

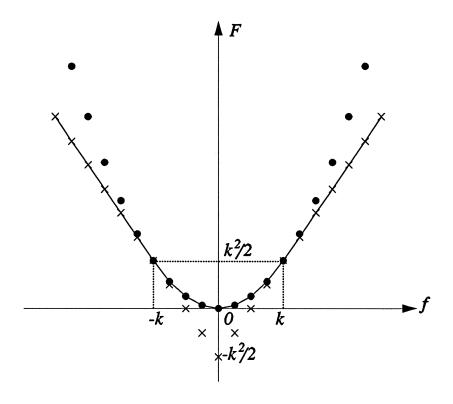
$$\sum_{j=1}^{m} \rho_k(f_j(\mathbf{\Phi}))$$

a hybrid of the  $\ell_2$  and the  $\ell_1$  norms



## Huber Function as a Hybrid of $\ell_1$ and $\ell_2$

the Huber,  $\ell_1$  and  $\ell_2$  objective functions in the one-dimensional case



the large errors are treated in the  $\ell_1$  sense and the small errors are measured in terms of least squares

by selecting k we can control the proportion of errors treated in the  $\ell_1$  or  $\ell_2$  sense



#### **One-Sided Huber Function**

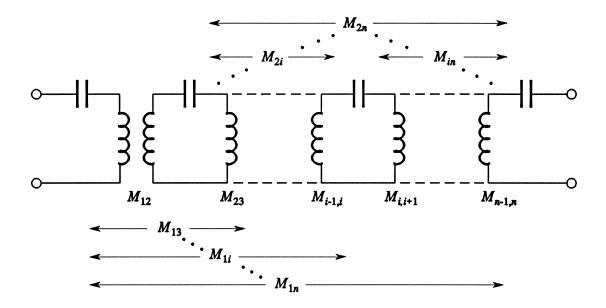
we extend the Huber concept by introducing a "one-sided" Huber function for design optimization with upper and/or lower specifications

we define the "one-sided" Huber function as

$$\rho_{k}^{+}(f) = \begin{cases} 0 & \text{if } f \leq 0 \\ \rho_{k}(f) & \text{if } f > 0 \end{cases}$$



## A 6th Order Multicavity Filter



the input reflection coefficient is used as simulated measurement

two large errors are deliberately introduced into data

the task is to identify the parameters from the contaminated data



# **Results of Parameter Identification for the Multicavity Filter - Case A**

the two large errors are the only errors contained in the data

Couplings	$M_{12}$	$M_{45}$	$M_{16}$	
Actual Values	0.859956	0.526602	0.087293	
Starting Point	0.819006	0.511264	0.093863	
$\ell_2$	-11%	7.3%	278%	
$\ell_1$	0.05%	-0.06%	-0.01%	
Huber	0.02%	0.01%	-1.2%	

the  $\ell_2$  solution is hopelessly corrupted by the wild data points



# **Results of Parameter Identification for the Multicavity Filter - Case B**

the data is truncated to the first two significant digits to emulate the limited accuracy of measurement equipment

Couplings	$M_{12}$	$M_{45}$	<i>M</i> <sub>16</sub>
Actual Values	0.859956	0.526602	0.087293
Starting Point	0.819006	0.511264	0.093863
$\ell_1$	0.51%	-2.9%	-14%
Huber	0.15%	-0.01%	-8.3%

 $\ell_1$  is more affected by small variations in the data

Huber solution less affected by small variations in the data



# **Results of Parameter Identification for the Multicavity Filter - Case C**

small errors randomly generated from the uniform distribution [-0.01 0.01] are introduced into the data

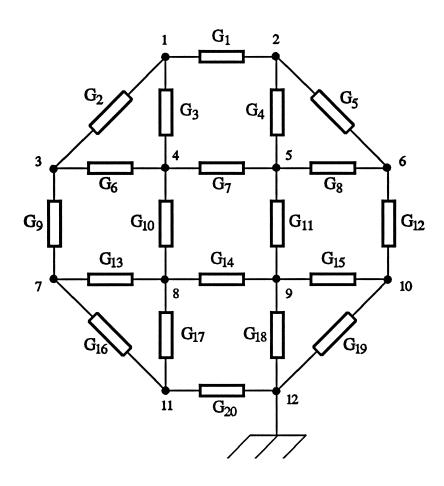
Couplings	$M_{12}$	$M_{45}$	$M_{16}$
Actual Values	0.859956	0.526602	0.087293
Starting Point	0.819006	0.511264	0.093863
$\ell_1$	1.8%	-4.1%	-43%
Huber	0.41%	0.04%	-27%

 $\ell_1$  is more affected by small variations in the data

Huber solution less affected by small variations in the data



#### A Resistive Mesh Circuit



used to demonstrate the  $\ell_1$  approach to analog fault location

we present new results which take into account data truncation errors representing limited accuracy of measurement equipment

## **Analog Fault Location of the Resistive Mesh Circuit**

 $\ell_1$  optimization attempts to suppress as many parameter deviations as possible to exactly zero

this may lead to an incorrect solution

two faults were assumed, namely  $G_2$  and  $G_{18}$ 

simulated node voltage measurements were generated at the accessible nodes

these voltages were truncated to the first two significant digits



### **Results of Fault Location of the Resistive Mesh Circuit**

Element			Perce	Percentage Deviation		
	Nominal Value	Actual Value	Actual	$\ell_1$	Huber	
$G_2$	1.0	0.50	-50.0	-47.55	-54.40	
$G_3^-$	1.0	1.05	5.0	-25.45	-3.68	
$G_{16}$	1.0	0.95	-5.0	-20.24	-3.53	
$G_{17}$	1.0	1.05	5.0	0.00	-0.81	
$G_{18}$	1.0	0.50	-50.0	-8.90	-49.97	
$G_{19}$	1.0	0.95	-5.0	-25.32	-4.74	
$G_{20}$	1.0	0.95	-5.0	-20.73	-5.98	

the nominal parameter values are used as the starting point for optimization

 $\ell_1$  optimization fails to isolate the faults

Huber optimization successfully isolates the faults



### Robustness Against "Bad" Starting Points in Optimization

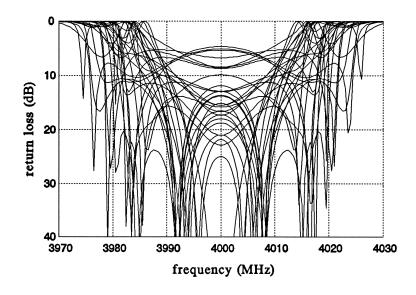
we show that the one-sided Huber function can be used in a "preprocessing" optimization to overcome bad starting points

6th-order multicavity filter

30 starting points generated using uniform distribution centered at a "good" starting point

±30% spread of the parameter values

the input return loss of the filter at the 30 starting points





#### **One-sided Huber Preprocessing of Arbitrary Starting Points**

from a "bad" starting point, a minimax optimizer can be trapped by the initial large errors

we have exploited the potential of using one-sided Huber preprocessing to overcome bad starting points in large-scale multiplexer optimization

here we expand our investigation by testing several starting points for optimization

we compare minimax optimization with and without onesided Huber preprocessing from these randomly generated starting points

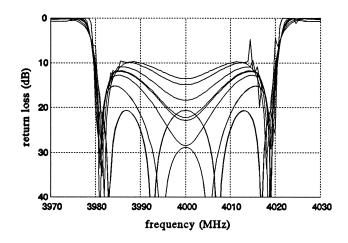
from each starting point, we perform:

- (1) direct minimax optimization
- (2) one-sided Huber optimization (preprocessing) followed by minimax optimization

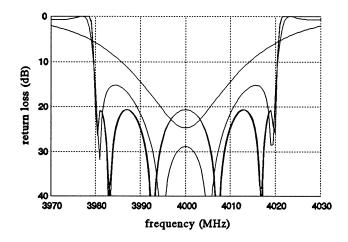


## **Results of One-sided Huber Preprocessing**

## without Huber preprocessing



## with Huber preprocessing



one-sided Huber preprocessing produces more focused results



### **Statistical Device Modeling**

parameter extraction/statistical postprocessing

first, we extract model parameters for individual devices from device measurements

then the sample of model parameters is postprocessed to estimate the statistics

for postprocessing we normally apply least-squares estimators

wild points severely degrade the least-squares estimates; in our earlier work using the  $\ell_2$  estimator the wild points had to be manually excluded

the Huber function can be used as an automatic robust statistical estimator in place of least-squares estimators

applying Huber estimators to the same data we obtained similar results but without excluding any points



#### **Statistical Estimation**

the error functions to estimate mean values

$$f_j(\overline{\Phi}) = \overline{\Phi} - \Phi^j$$

the error functions to estimate standard deviations

$$f_j(V_{\Phi}) = V_{\Phi} - (\Phi^j - \overline{\Phi})^2$$

where

 $\phi^{j}$  the extracted value of a parameter of the jth device

*j* 1, 2, ..., *N* 

N the total number of devices

 $V_{\phi}$  the estimated variance from which we can calculate the standard deviation  $\sigma_{\phi}$ 



## **One-sided Huber Formulation for Yield Optimization**

we present a one-sided Huber approach to yield optimization of linear and nonlinear circuits

we consider a number of statistical outcomes of circuit parameters denoted by  $\phi^i$ 

for each outcome we create a generalized  $\ell_p$  function  $\nu(\mathbf{\Phi}^i)$ 

we have formulated yield optimization as a one-sided  $\ell_1$  problem (Bandler and Chen, 1988)

here we formulate yield optimization as a one-sided Huber problem: the objective function is defined as

$$U(\mathbf{\Phi}^0) = \sum_{i=1}^{N} \rho_k^+(\alpha_i \nu(\mathbf{\Phi}^i))$$

where

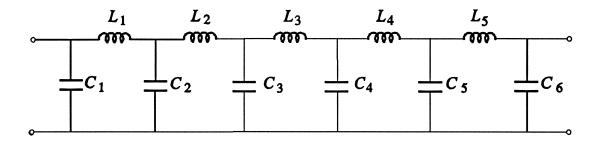
 $\phi^0$  the nominal circuit parameters

 $\alpha_i$  a positive multiplier associated with the *i*th outcome

N the total number of outcomes



### Yield Optimization of an LC Filter



one-sided  $\ell_1$  method needed 160 CPU seconds (11 iterations)

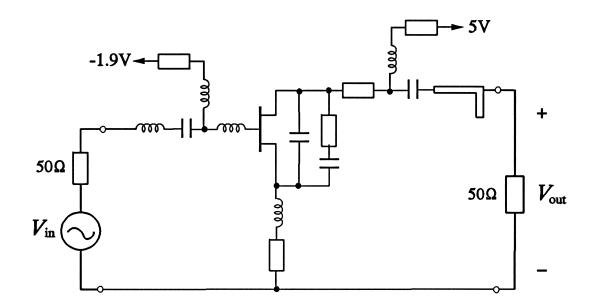
one-sided Huber yield optimization with k=0.2 finished in 123 CPU seconds (9 iterations)

both optimizations produced 75% yield

Sun SPARCstation 10



#### Yield Optimization of a Nonlinear Frequency Doubler



uniform distributions in the linear matching subcircuits; normal distributions for the intrinsic FET

one-sided  $\ell_1$  centering finished in 17 iterations and 337 CPU seconds and increased yield from 28% to 76%

one-sided Huber centering finished in 29 iterations and 574 CPU seconds and increased yield from 28% to 77%

Sun SPARCstation 10



#### **Conclusions**

exciting applications of a novel Huber approach to

parameter identification
analog fault location
preprocessing of arbitrary starting points
statistical modeling
statistical design centering

the Huber approach demonstrates robustness and consistency in the presence of large and small errors, both deterministic and statistical

it combines the advantages of  $\ell_1$  and  $\ell_2$  techniques and overcomes their respective shortcomings

the Huber concept is consistent with practical engineering intuition

the Huber method will have a far-reaching and profound impact on modeling, design, design validation, fault diagnosis and statistical modeling and design