

**AGGRESSIVE SPACE MAPPING WITH MULTIPLE POINT  
PARAMETER EXTRACTION: A STEP BY  
STEP ILLUSTRATION USING TWO  
ROSENBROCK FUNCTIONS**

J.W. Bandler and J.E. Rayas-Sánchez

SOS-98-27-V

August 1998

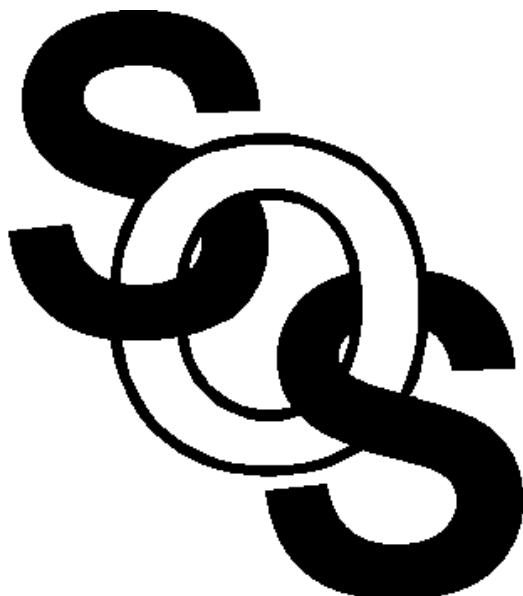
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**AGGRESSIVE SPACE MAPPING WITH MULTIPLE  
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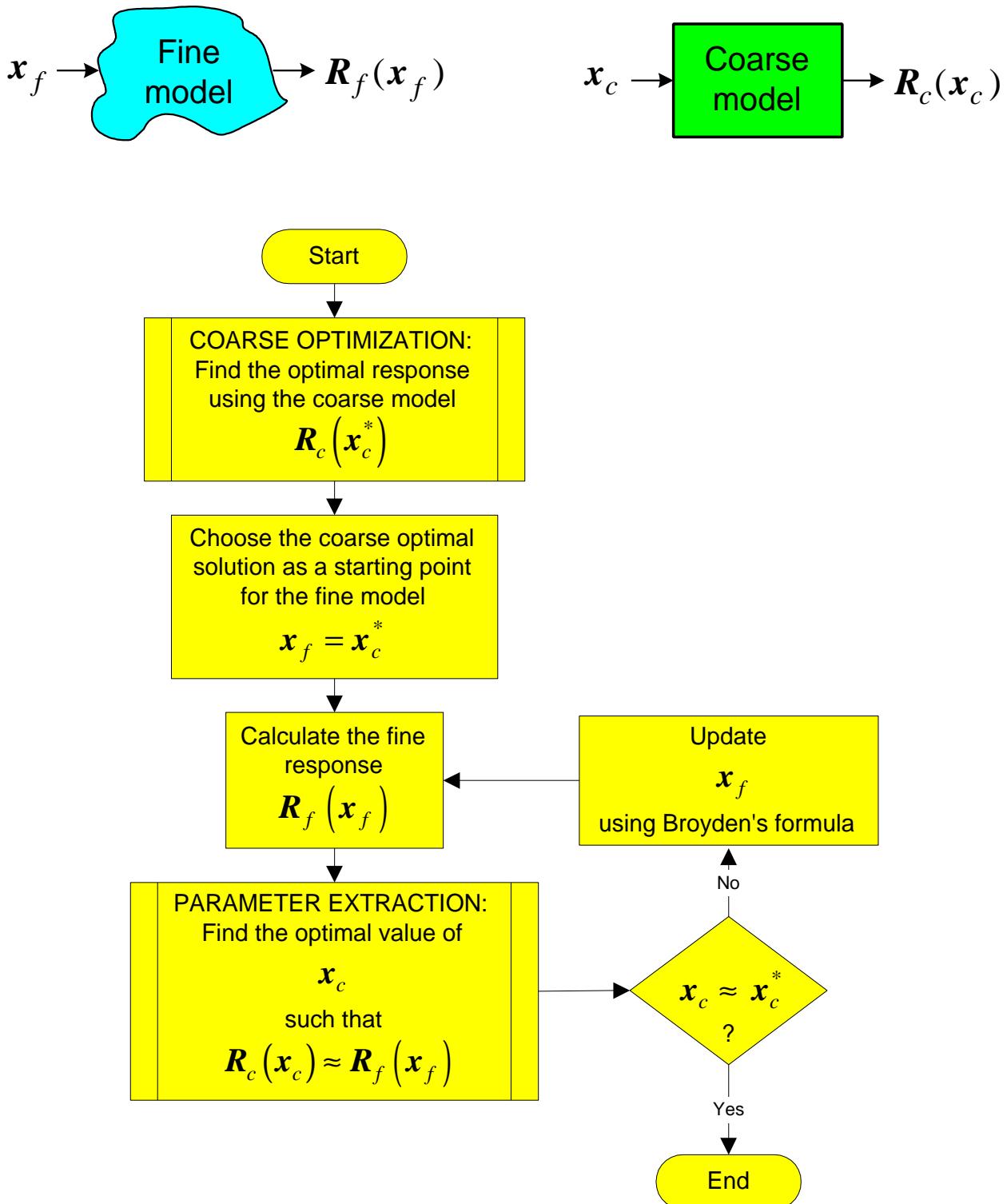
Simulation Optimization Systems Research Laboratory  
and Department of Electrical and Computer Engineering  
McMaster University, Hamilton, Canada L8S 4L7



presented at

SOS Research Laboratory Meeting, Hamilton, August 12, 1998

## Aggressive Space Mapping (ASM) Concept



## ASM Algorithm (Bandler *et al.*, 1995)

*Step 0.* Initialize  $\mathbf{x}_f^{(1)} = \mathbf{x}_c^*, \mathbf{B}^{(1)} = \mathbf{I}, j = 1$ .

*Step 1.* Evaluate  $\mathbf{R}_f(\mathbf{x}_f^{(1)})$ .

*Step 2.* Extract  $\mathbf{x}_c^{(1)}$  such that  $\mathbf{R}_c(\mathbf{x}_c^{(1)}) \approx \mathbf{R}_f(\mathbf{x}_f^{(1)})$ .

*Step 3.* Evaluate  $\mathbf{f}^{(1)} = \mathbf{x}_c^{(1)} - \mathbf{x}_c^*$ . Stop if  $\|\mathbf{f}^{(1)}\| \leq \mathbf{h}$ .

*Step 4.* Solve  $\mathbf{B}^{(j)} \mathbf{h}^{(j)} = -\mathbf{f}^{(j)}$  for  $\mathbf{h}^{(j)}$ .

*Step 5.* Set  $\mathbf{x}_f^{(j+1)} = \mathbf{x}_f^{(j)} + \mathbf{h}^{(j)}$ .

*Step 6.* Evaluate  $\mathbf{R}_f(\mathbf{x}_f^{(j+1)})$ .

*Step 7.* Extract  $\mathbf{x}_c^{(j+1)}$  such that  $\mathbf{R}_c(\mathbf{x}_c^{(j+1)}) \approx \mathbf{R}_f(\mathbf{x}_f^{(j+1)})$ .

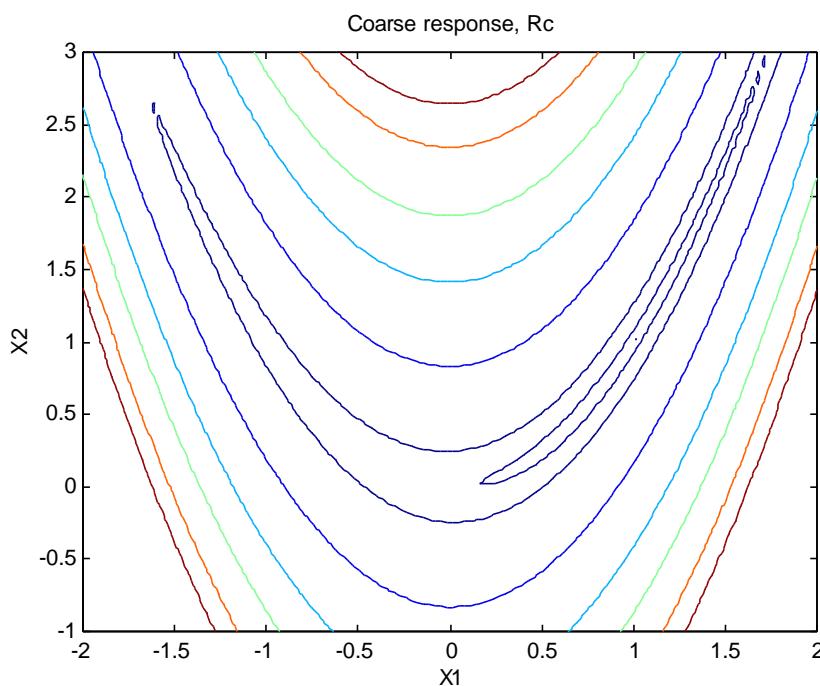
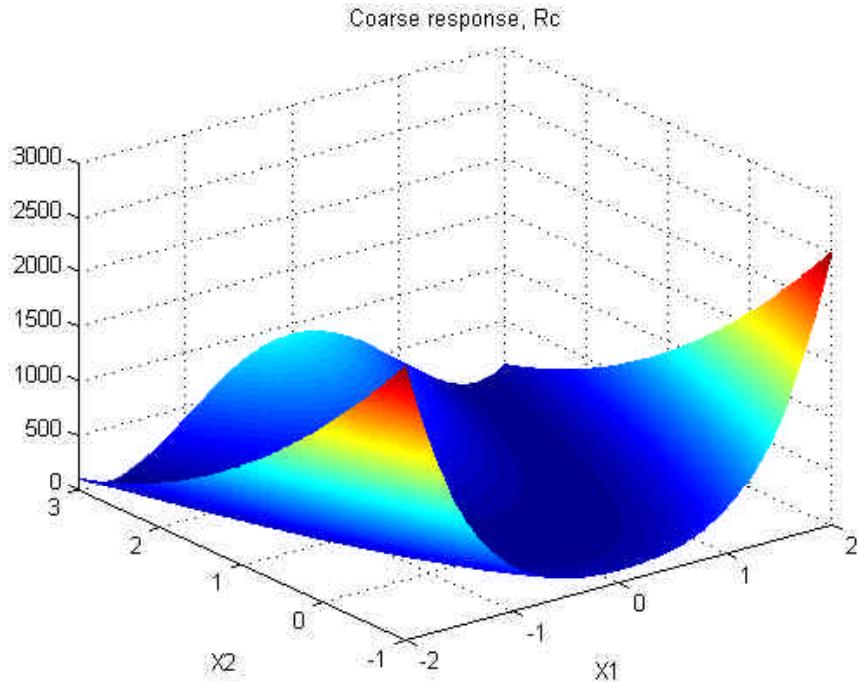
*Step 8.* Evaluate  $\mathbf{f}^{(j+1)} = \mathbf{x}_c^{(j+1)} - \mathbf{x}_c^*$ . Stop if  $\|\mathbf{f}^{(j+1)}\| \leq \mathbf{h}$ .

*Step 9.* Update  $\mathbf{B}^{(j+1)} = \mathbf{B}^{(j)} + \frac{\mathbf{f}^{(j+1)} \mathbf{h}^{(j)T}}{\mathbf{h}^{(j)T} \mathbf{h}^{(j)}}$ .

*Step 10.* Set  $j = j + 1$ ; go to *Step 4*.

## Coarse Model: Rosenbrock Function

$$R_c(x) = 100(x_2 - x_1^2)^2 + (1 - x_1)^2, \text{ where } x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

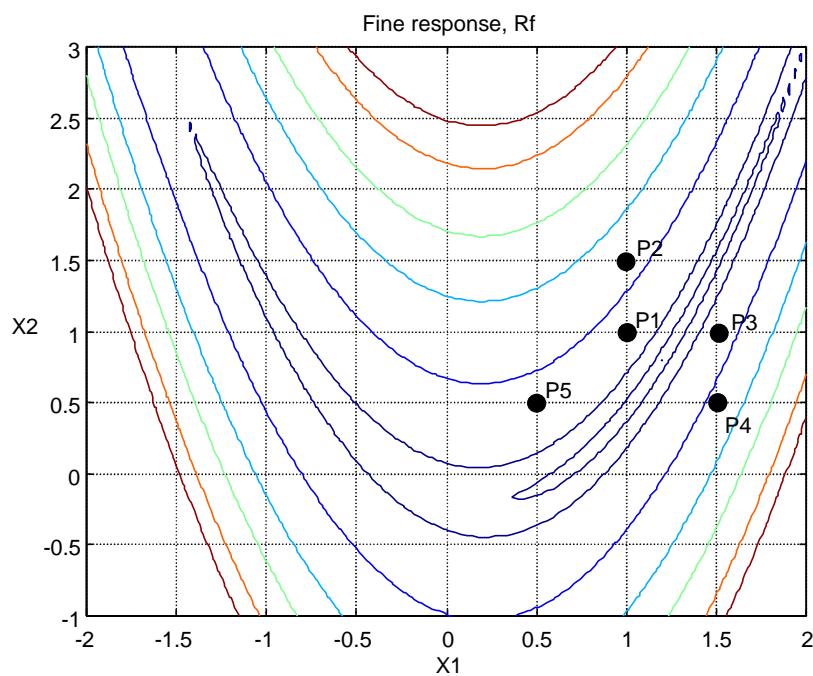
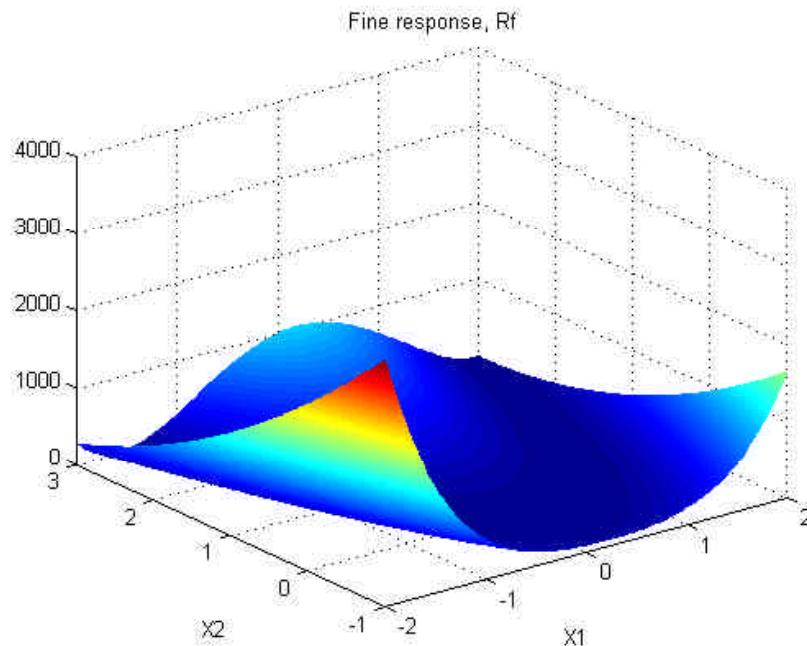


$$\mathbf{x}_c^* = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$R_c^* = R_c(\mathbf{x}_c^*) = 0$$

## Fine Model: Perturbed Rosenbrock Function

$$R_f(x) = 100(u_2 - u_1^2)^2 + (1-u_1)^2 \text{ where } \mathbf{u} = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} = \mathbf{x} + \begin{bmatrix} -0.2 \\ +0.2 \end{bmatrix}$$



## Multiple Point Parameter Extraction

Instead of minimizing  $\|R_c(\mathbf{x}) - R_f(\mathbf{x}_c^*)\|_p$  we will minimize a

parameter extraction objective function considering five matching points

$$\|R_c(\mathbf{x} + \mathbf{B}^{(j)}? \mathbf{x}_i) - R_f(\mathbf{x}_c^* + ? \mathbf{x}_i)\|_p , \text{ where}$$

$$\Delta \mathbf{x}_1 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_2 = \begin{bmatrix} 0 \\ 0.5 \end{bmatrix}, \Delta \mathbf{x}_3 = \begin{bmatrix} 0.5 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_4 = \begin{bmatrix} 0.5 \\ -0.5 \end{bmatrix}, \Delta \mathbf{x}_5 = \begin{bmatrix} -0.5 \\ -0.5 \end{bmatrix}$$

Since the matrix  $\mathbf{B}^{(j)} = \mathbf{I}$  for the first parameter extraction optimization,

the corresponding five error functions  $E_i$  are given by

$$E_i = R_c(\mathbf{x} + ? \mathbf{x}_i) - R_f(\mathbf{x}_c^* + ? \mathbf{x}_i)$$

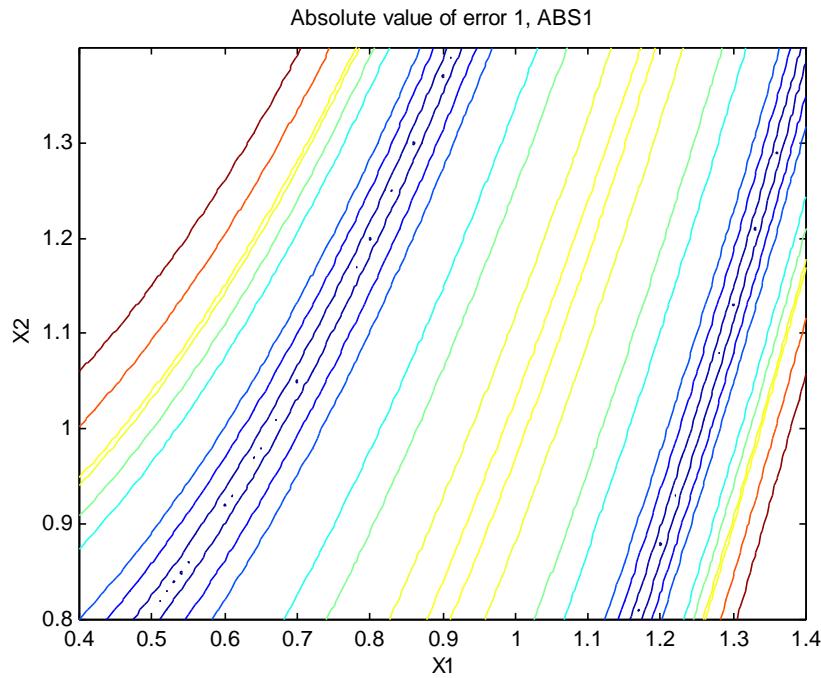
Considering only  $l_1$  and  $l_2$  norms, the corresponding objective functions

are

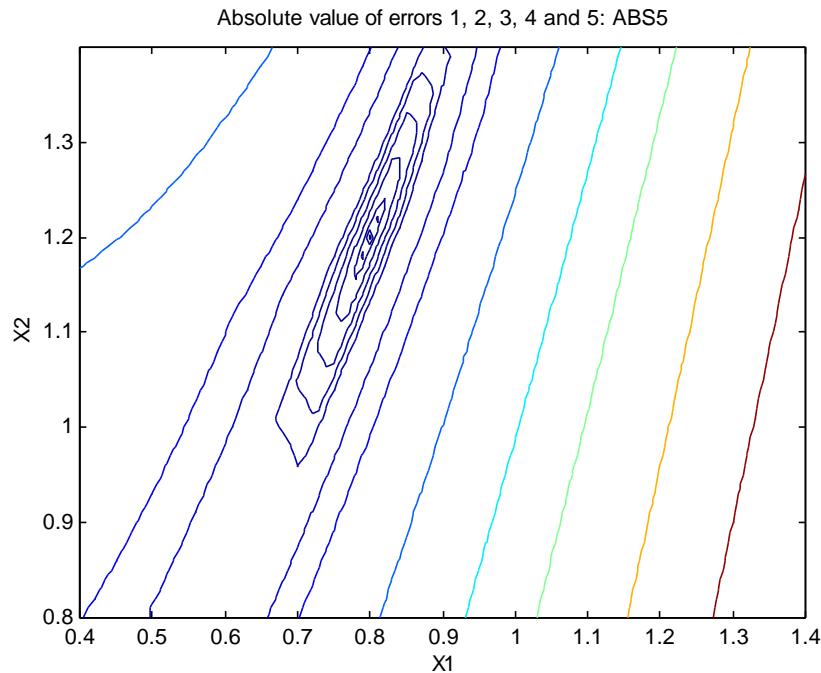
$$ABS_n = |E_1| + |E_2| + \dots + |E_n|$$

$$SQR_n = (E_1)^2 + (E_2)^2 + \dots + (E_n)^2$$

## $l_1$ Objective Function for the Parameter Extraction Problem

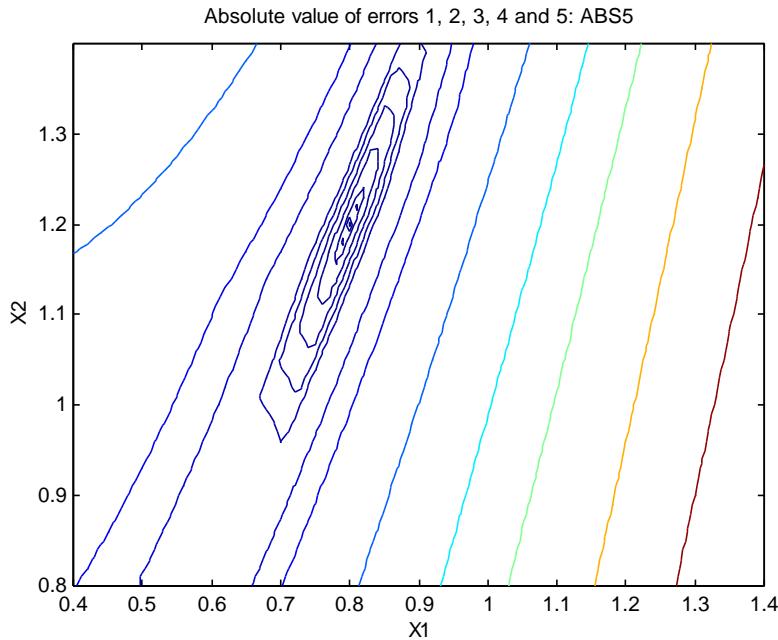


(a) single point parameter extraction

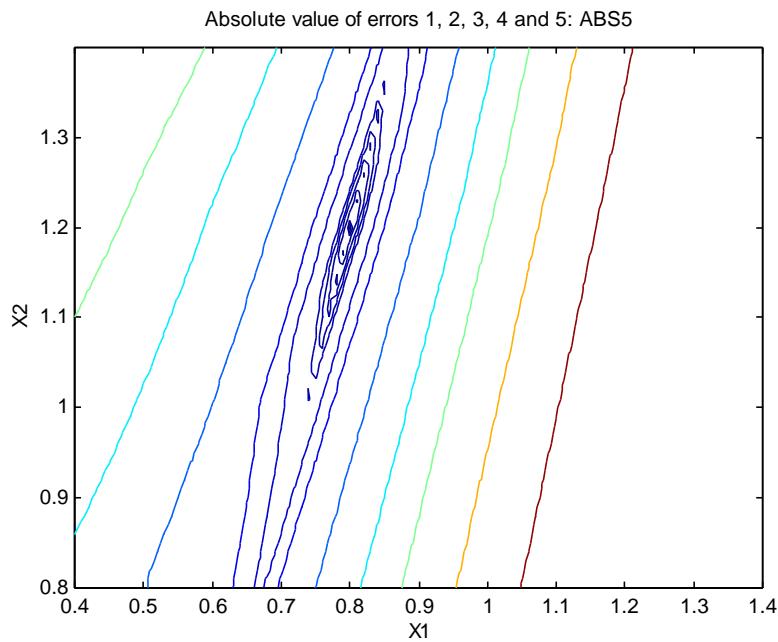


(b) multiple point parameter extraction (4 additional points)

## $l_1$ Objective Function for 5-point Parameter Extraction

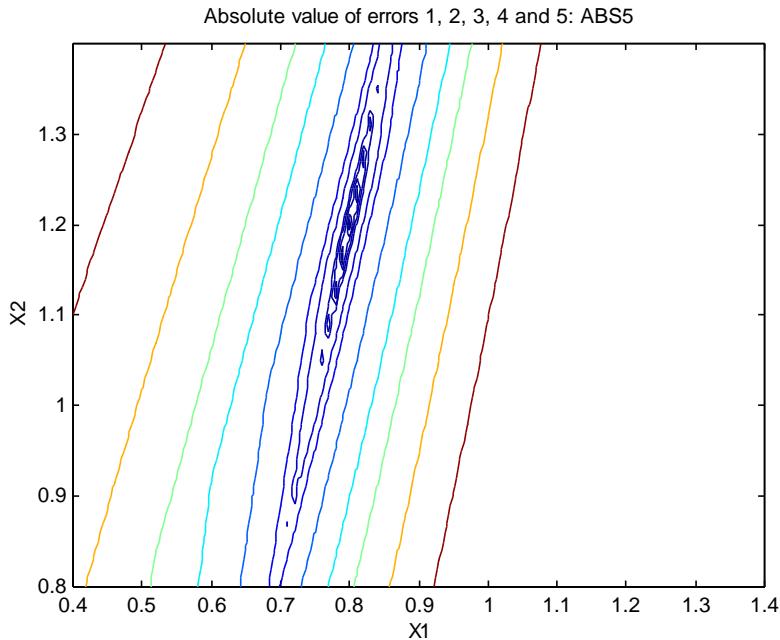


$$\Delta \mathbf{x}_1 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_2 = \begin{bmatrix} 0 \\ 0.5 \end{bmatrix}, \Delta \mathbf{x}_3 = \begin{bmatrix} 0.5 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_4 = \begin{bmatrix} 0.5 \\ -0.5 \end{bmatrix}, \Delta \mathbf{x}_5 = \begin{bmatrix} -0.5 \\ -0.5 \end{bmatrix}$$

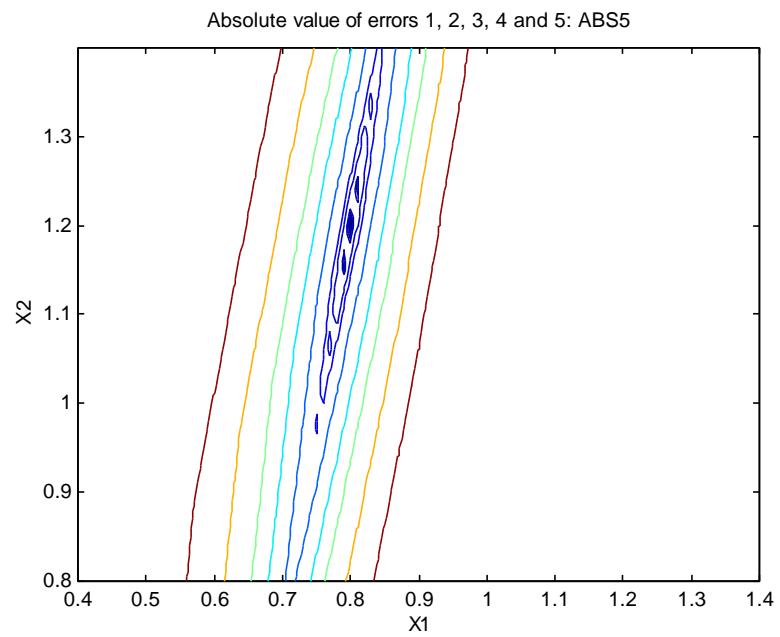


$$\Delta \mathbf{x}_1 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_2 = \begin{bmatrix} 0 \\ 0.8 \end{bmatrix}, \Delta \mathbf{x}_3 = \begin{bmatrix} 0.8 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_4 = \begin{bmatrix} 0.8 \\ -0.8 \end{bmatrix}, \Delta \mathbf{x}_5 = \begin{bmatrix} -0.8 \\ -0.8 \end{bmatrix}$$

## $l_1$ Objective Function for 5-point Parameter Extraction

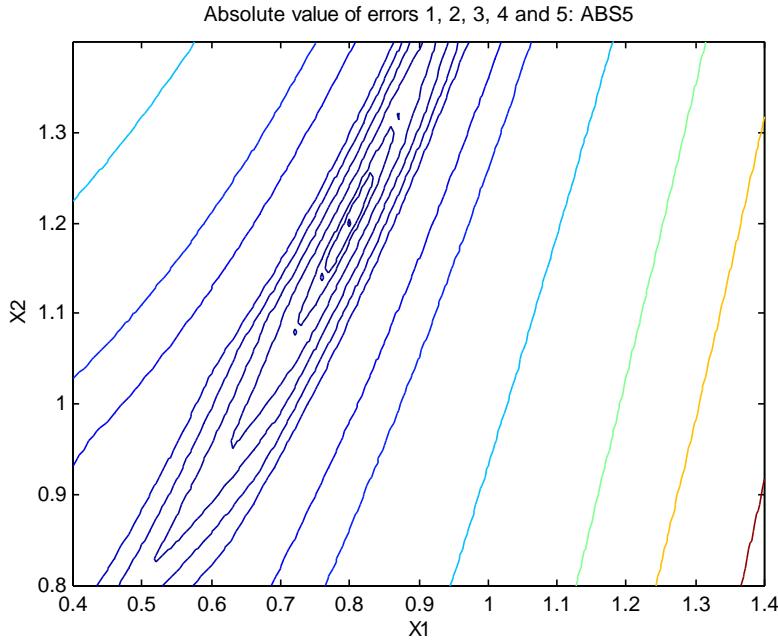


$$\Delta \mathbf{x}_1 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_2 = \begin{bmatrix} 0 \\ 1.1 \end{bmatrix}, \Delta \mathbf{x}_3 = \begin{bmatrix} 1.1 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_4 = \begin{bmatrix} 1.1 \\ -1.1 \end{bmatrix}, \Delta \mathbf{x}_5 = \begin{bmatrix} -1.1 \\ -1.1 \end{bmatrix}$$

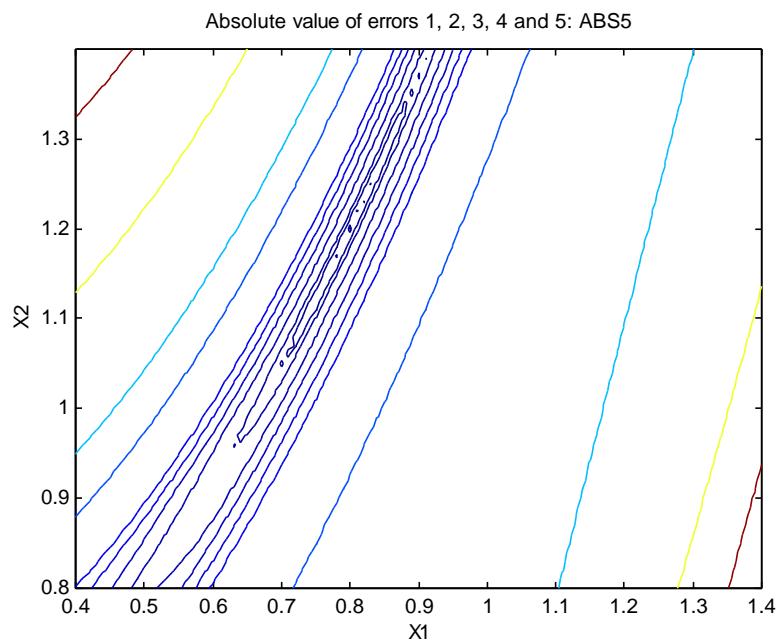


$$\Delta \mathbf{x}_1 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_2 = \begin{bmatrix} 0 \\ 1.5 \end{bmatrix}, \Delta \mathbf{x}_3 = \begin{bmatrix} 1.5 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_4 = \begin{bmatrix} 1.5 \\ -1.5 \end{bmatrix}, \Delta \mathbf{x}_5 = \begin{bmatrix} -1.5 \\ -1.5 \end{bmatrix}$$

## $l_1$ Objective Function for 5-point Parameter Extraction



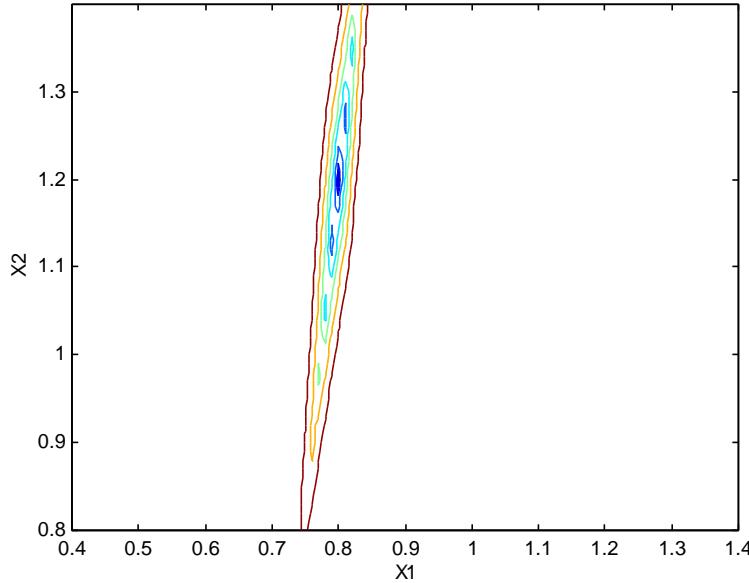
$$\Delta \mathbf{x}_1 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_2 = \begin{bmatrix} 0 \\ 0.3 \end{bmatrix}, \Delta \mathbf{x}_3 = \begin{bmatrix} 0.3 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_4 = \begin{bmatrix} 0.3 \\ -0.3 \end{bmatrix}, \Delta \mathbf{x}_5 = \begin{bmatrix} -0.3 \\ -0.3 \end{bmatrix}$$



$$\Delta \mathbf{x}_1 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_2 = \begin{bmatrix} 0 \\ 0.1 \end{bmatrix}, \Delta \mathbf{x}_3 = \begin{bmatrix} 0.1 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_4 = \begin{bmatrix} 0.1 \\ -0.1 \end{bmatrix}, \Delta \mathbf{x}_5 = \begin{bmatrix} -0.1 \\ -0.1 \end{bmatrix}$$

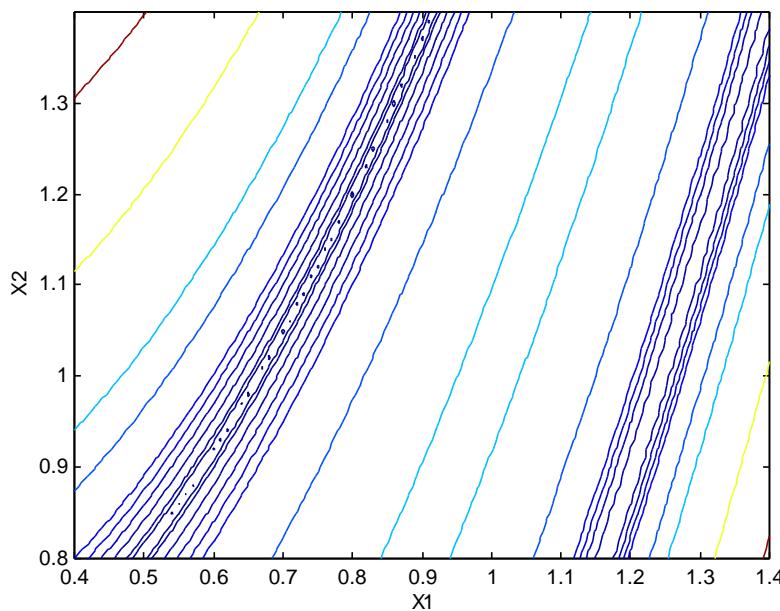
## **$l_1$ Objective Function for 5-point Parameter Extraction**

Absolute value of errors 1, 2, 3, 4 and 5: ABS5



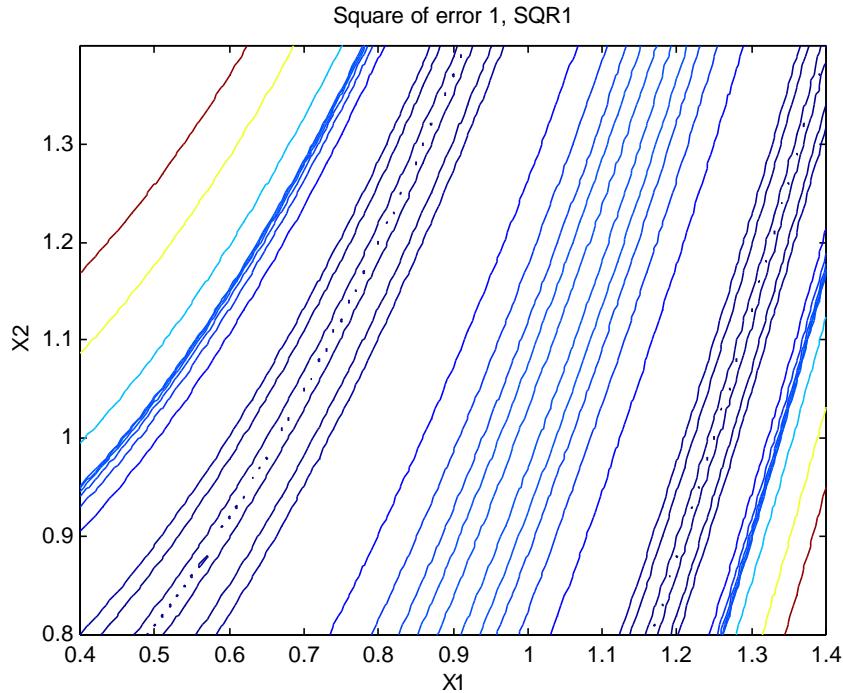
$$\Delta \mathbf{x}_1 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_2 = \begin{bmatrix} 0 \\ 3 \end{bmatrix}, \Delta \mathbf{x}_3 = \begin{bmatrix} 3 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_4 = \begin{bmatrix} 3 \\ -3 \end{bmatrix}, \Delta \mathbf{x}_5 = \begin{bmatrix} -3 \\ -3 \end{bmatrix}$$

Absolute value of errors 1, 2, 3, 4 and 5: ABS5

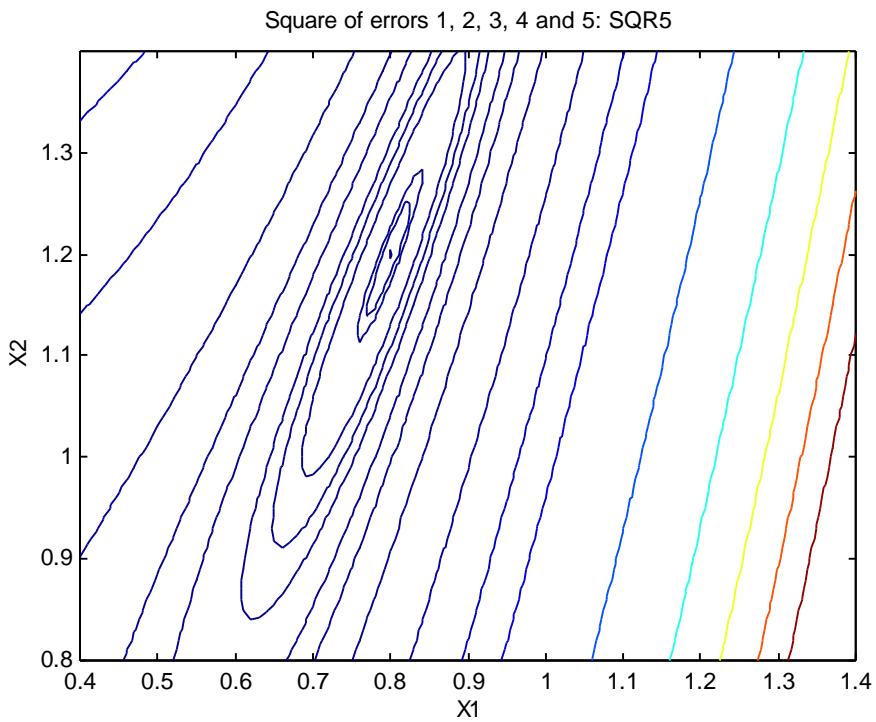


$$\Delta \mathbf{x}_1 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_2 = \begin{bmatrix} 0 \\ 0.01 \end{bmatrix}, \Delta \mathbf{x}_3 = \begin{bmatrix} 0.01 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_4 = \begin{bmatrix} 0.01 \\ -0.01 \end{bmatrix}, \Delta \mathbf{x}_5 = \begin{bmatrix} -0.01 \\ -0.01 \end{bmatrix}$$

## $l_2$ Objective Function for the Parameter Extraction Problem

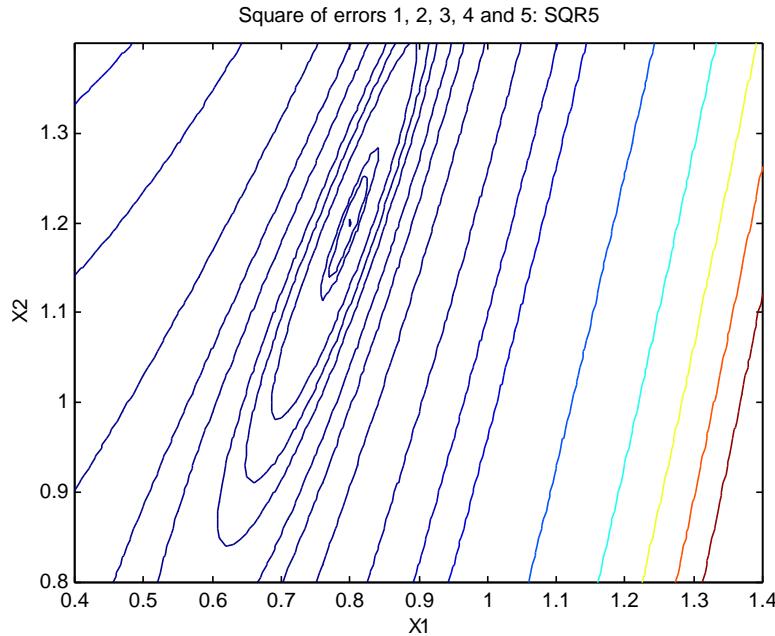


(a) single point parameter extraction

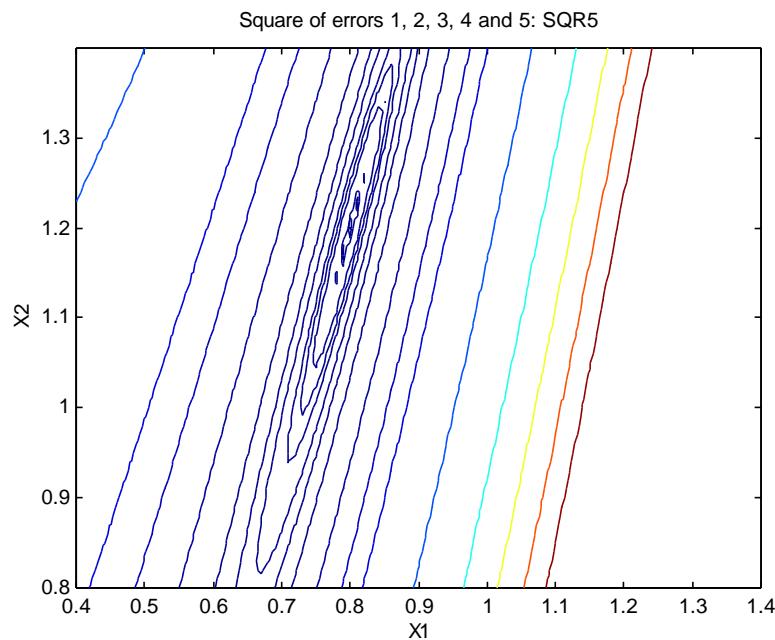


(b) multiple point parameter extraction (with 4 additional points)

## $l_2$ Objective Function for 5-point Parameter Extraction

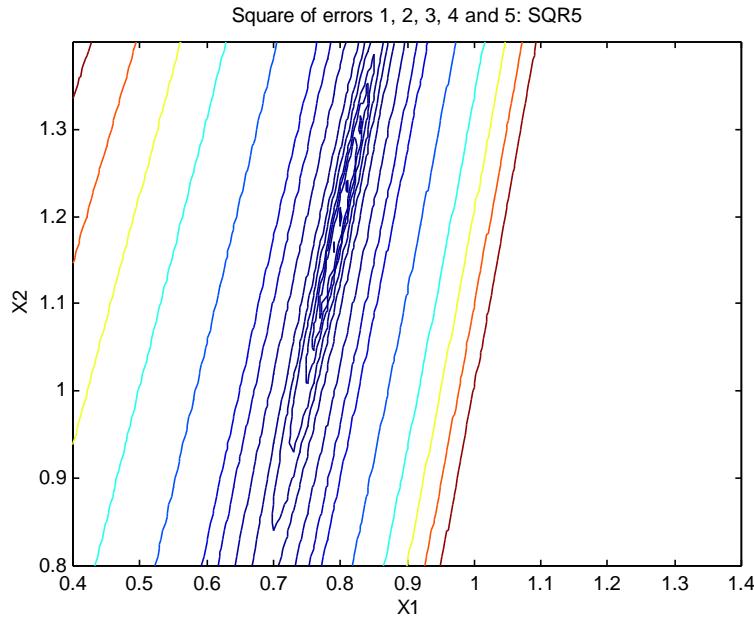


$$\Delta \mathbf{x}_1 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_2 = \begin{bmatrix} 0 \\ 0.5 \end{bmatrix}, \Delta \mathbf{x}_3 = \begin{bmatrix} 0.5 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_4 = \begin{bmatrix} 0.5 \\ -0.5 \end{bmatrix}, \Delta \mathbf{x}_5 = \begin{bmatrix} -0.5 \\ -0.5 \end{bmatrix}$$

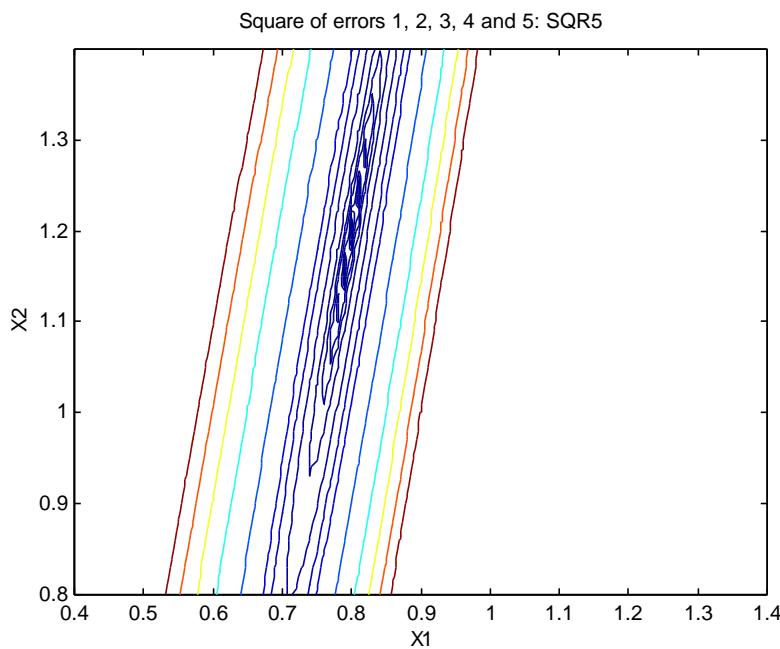


$$\Delta \mathbf{x}_1 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_2 = \begin{bmatrix} 0 \\ 0.8 \end{bmatrix}, \Delta \mathbf{x}_3 = \begin{bmatrix} 0.8 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_4 = \begin{bmatrix} 0.8 \\ -0.8 \end{bmatrix}, \Delta \mathbf{x}_5 = \begin{bmatrix} -0.8 \\ -0.8 \end{bmatrix}$$

## $l_2$ Objective Function for 5-point Parameter Extraction



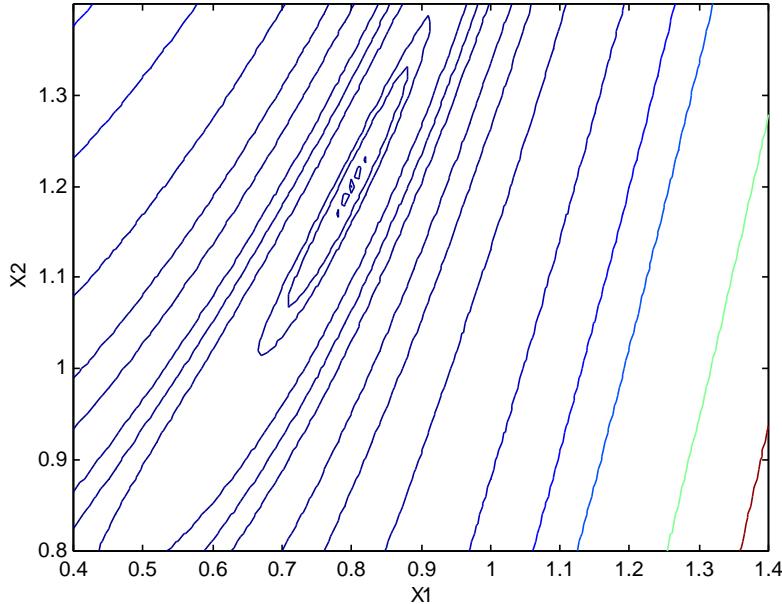
$$\Delta \mathbf{x}_1 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_2 = \begin{bmatrix} 0 \\ 1.1 \end{bmatrix}, \Delta \mathbf{x}_3 = \begin{bmatrix} 1.1 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_4 = \begin{bmatrix} 1.1 \\ -1.1 \end{bmatrix}, \Delta \mathbf{x}_5 = \begin{bmatrix} -1.1 \\ -1.1 \end{bmatrix}$$



$$\Delta \mathbf{x}_1 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_2 = \begin{bmatrix} 0 \\ 1.5 \end{bmatrix}, \Delta \mathbf{x}_3 = \begin{bmatrix} 1.5 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_4 = \begin{bmatrix} 1.5 \\ -1.5 \end{bmatrix}, \Delta \mathbf{x}_5 = \begin{bmatrix} -1.5 \\ -1.5 \end{bmatrix}$$

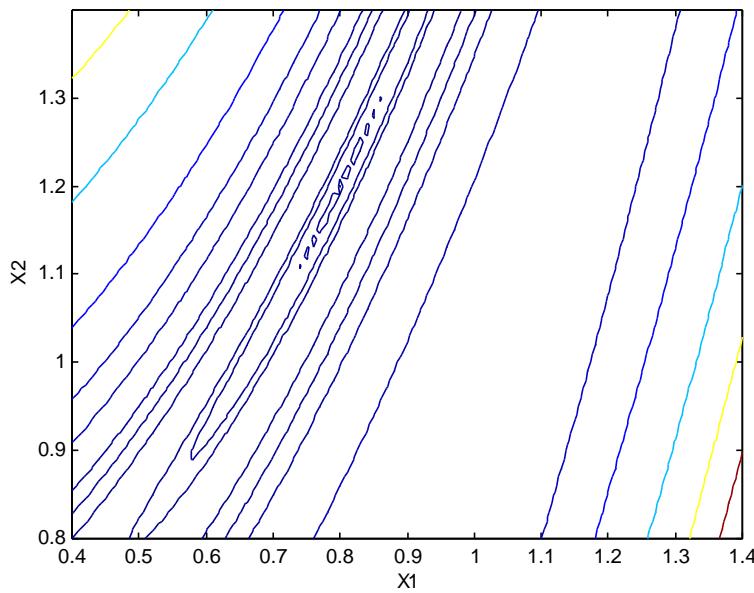
## $l_2$ Objective Function for 5-point Parameter Extraction

Square of errors 1, 2, 3, 4 and 5: SQR5



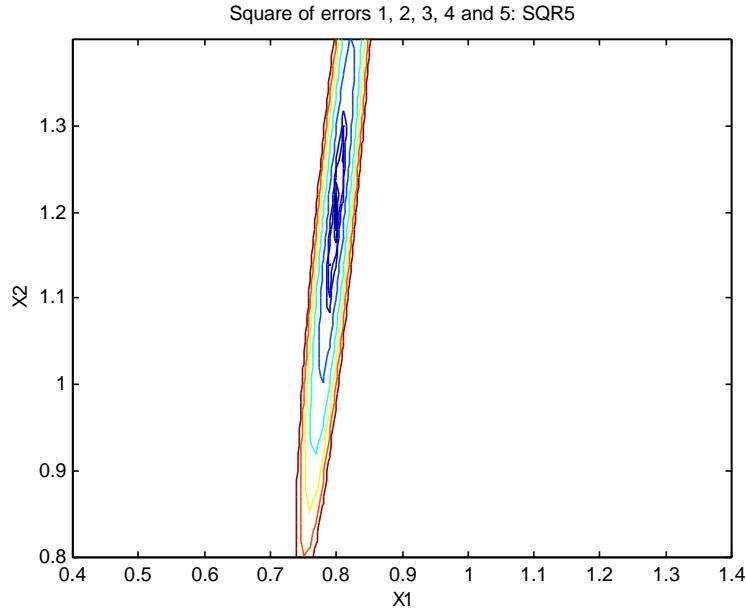
$$\Delta \mathbf{x}_1 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_2 = \begin{bmatrix} 0 \\ 0.3 \end{bmatrix}, \Delta \mathbf{x}_3 = \begin{bmatrix} 0.3 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_4 = \begin{bmatrix} 0.3 \\ -0.3 \end{bmatrix}, \Delta \mathbf{x}_5 = \begin{bmatrix} -0.3 \\ -0.3 \end{bmatrix}$$

Square of errors 1, 2, 3, 4 and 5: SQR5

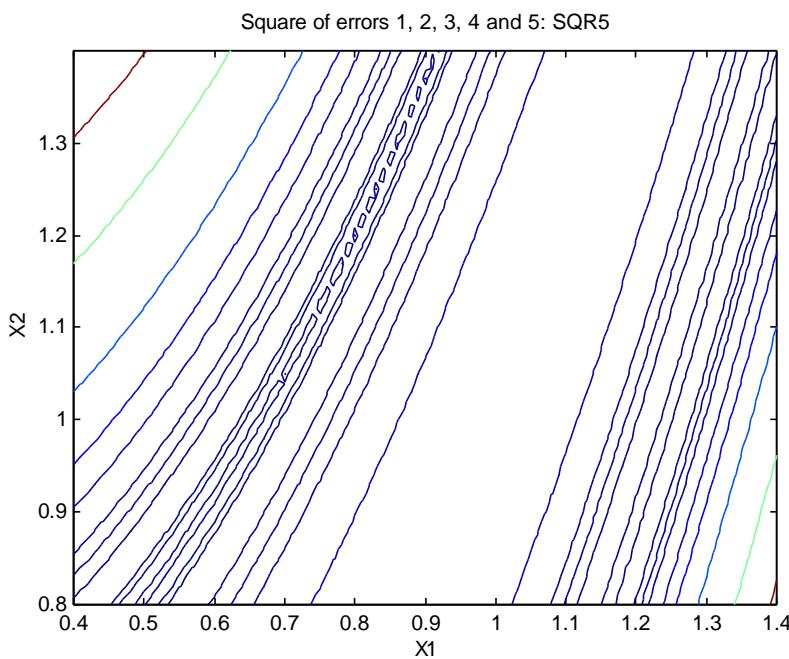


$$\Delta \mathbf{x}_1 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_2 = \begin{bmatrix} 0 \\ 0.1 \end{bmatrix}, \Delta \mathbf{x}_3 = \begin{bmatrix} 0.1 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_4 = \begin{bmatrix} 0.1 \\ -0.1 \end{bmatrix}, \Delta \mathbf{x}_5 = \begin{bmatrix} -0.1 \\ -0.1 \end{bmatrix}$$

## $l_2$ Objective Function for 5-point Parameter Extraction



$$\Delta \mathbf{x}_1 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_2 = \begin{bmatrix} 0 \\ 3 \end{bmatrix}, \Delta \mathbf{x}_3 = \begin{bmatrix} 3 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_4 = \begin{bmatrix} 3 \\ -3 \end{bmatrix}, \Delta \mathbf{x}_5 = \begin{bmatrix} -3 \\ -3 \end{bmatrix}$$



$$\Delta \mathbf{x}_1 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_2 = \begin{bmatrix} 0 \\ 0.01 \end{bmatrix}, \Delta \mathbf{x}_3 = \begin{bmatrix} 0.01 \\ 0 \end{bmatrix}, \Delta \mathbf{x}_4 = \begin{bmatrix} 0.01 \\ -0.01 \end{bmatrix}, \Delta \mathbf{x}_5 = \begin{bmatrix} -0.01 \\ -0.01 \end{bmatrix}$$

It can be visualized from the plots of  $ABS_5$  and  $SQR_5$  that the solution

for the parameter extraction problem is  $\mathbf{x} = \begin{bmatrix} 0.8 \\ 1.2 \end{bmatrix}$ . It can also be

verified that

$$R_c \left( \begin{bmatrix} 0.8 \\ 1.2 \end{bmatrix} + ? \mathbf{x}_1 \right) = R_f (\mathbf{x}_c^* + ? \mathbf{x}_1) = 31.4,$$

$$R_c \left( \begin{bmatrix} 0.8 \\ 1.2 \end{bmatrix} + ? \mathbf{x}_2 \right) = R_f (\mathbf{x}_c^* + ? \mathbf{x}_2) = 112.4,$$

$$R_c \left( \begin{bmatrix} 0.8 \\ 1.2 \end{bmatrix} + ? \mathbf{x}_3 \right) = R_f (\mathbf{x}_c^* + ? \mathbf{x}_3) = 24.1 ,$$

$$R_c \left( \begin{bmatrix} 0.8 \\ 1.2 \end{bmatrix} + ? \mathbf{x}_4 \right) = R_f (\mathbf{x}_c^* + ? \mathbf{x}_4) = 98.1, \text{ and}$$

$$R_c \left( \begin{bmatrix} 0.8 \\ 1.2 \end{bmatrix} + ? \mathbf{x}_5 \right) = R_f (\mathbf{x}_c^* + ? \mathbf{x}_5) = 37.7$$

## Space Mapped Solution

$$Step \ 0. \quad \mathbf{x}_f^{(1)} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \ \mathbf{B}^{(1)} = \mathbf{I}, \ j=1$$

$$Step \ 1. \quad R_f(\mathbf{x}_f^{(1)}) = 31.4$$

$$Step \ 2. \quad \text{When } \mathbf{x}_c^{(1)} = \begin{bmatrix} 0.8 \\ 1.2 \end{bmatrix}, \ R_c(\mathbf{x}_c^{(1)}) = R_f(\mathbf{x}_f^{(1)})$$

$$Step \ 3. \quad \mathbf{f}^{(1)} = \begin{bmatrix} 0.8 \\ 1.2 \end{bmatrix} - \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} -0.2 \\ 0.2 \end{bmatrix}$$

$$Step \ 4. \quad \text{Since } \mathbf{B}^{(1)} = \mathbf{I}, \ \mathbf{h}^{(1)} = \begin{bmatrix} 0.2 \\ -0.2 \end{bmatrix}$$

$$Step \ 5. \quad \text{Set } \mathbf{x}_f^{(2)} = \begin{bmatrix} 1 \\ 1 \end{bmatrix} + \begin{bmatrix} 0.2 \\ -0.2 \end{bmatrix} = \begin{bmatrix} 1.2 \\ 0.8 \end{bmatrix}$$

$$Step \ 6. \quad R_f(\mathbf{x}_f^{(2)}) = 0$$

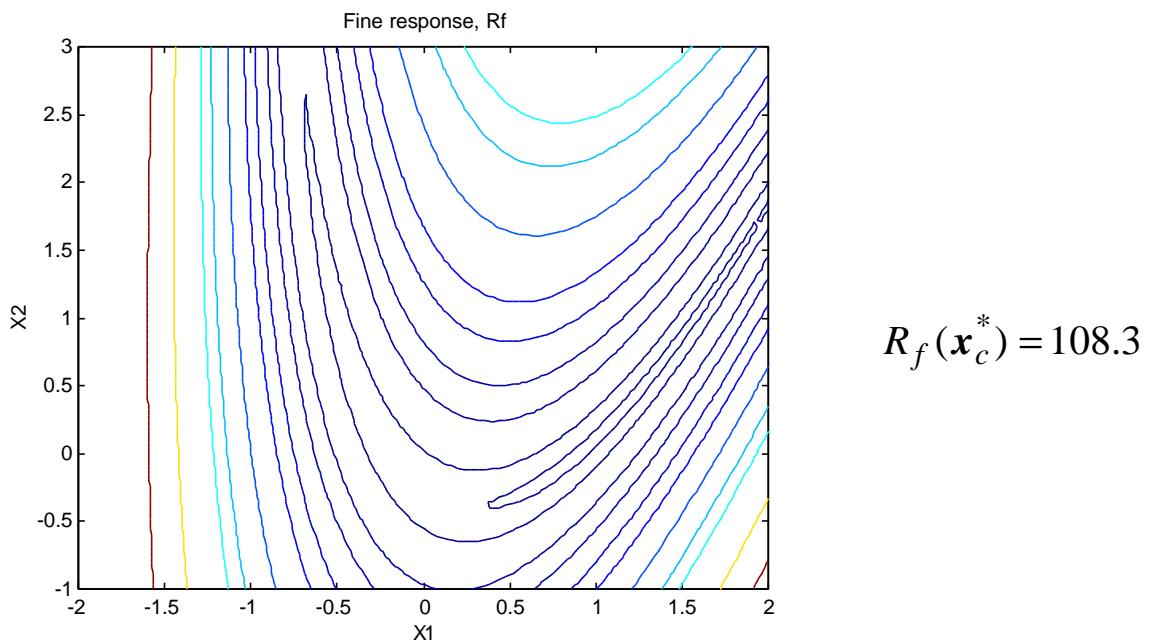
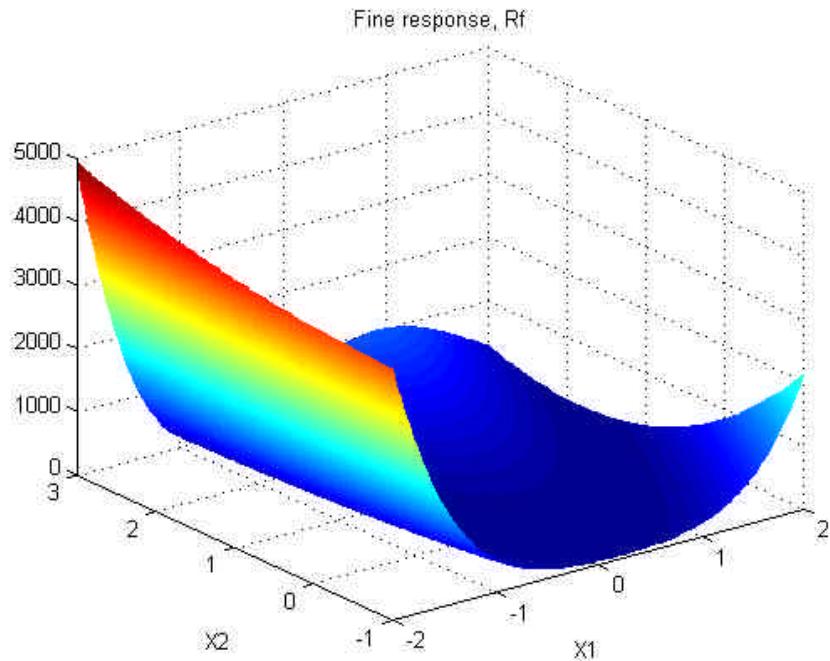
$$Step \ 7. \quad \mathbf{x}_c^{(2)} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \text{ because we know } R_c(\mathbf{x}_c^{(2)}) = 0$$

$$Step \ 8. \quad \text{Since } \mathbf{f}^{(2)} = \mathbf{x}_c^{(2)} - \mathbf{x}_c^* = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \text{ then } \bar{\mathbf{x}}_f = \mathbf{x}_f^{(2)} = \begin{bmatrix} 1.2 \\ 0.8 \end{bmatrix}$$

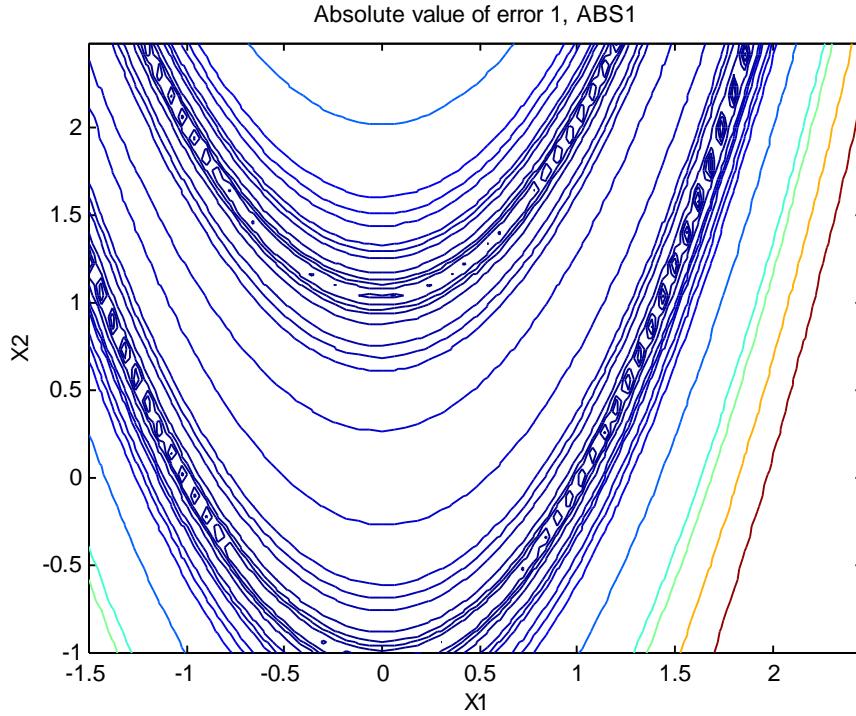
## 2<sup>nd</sup> Fine Model: Perturbed Rosenbrock Function

$$R_f(x) = 100(u_2 - u_1^2)^2 + (1 - u_1)^2 \quad \text{where}$$

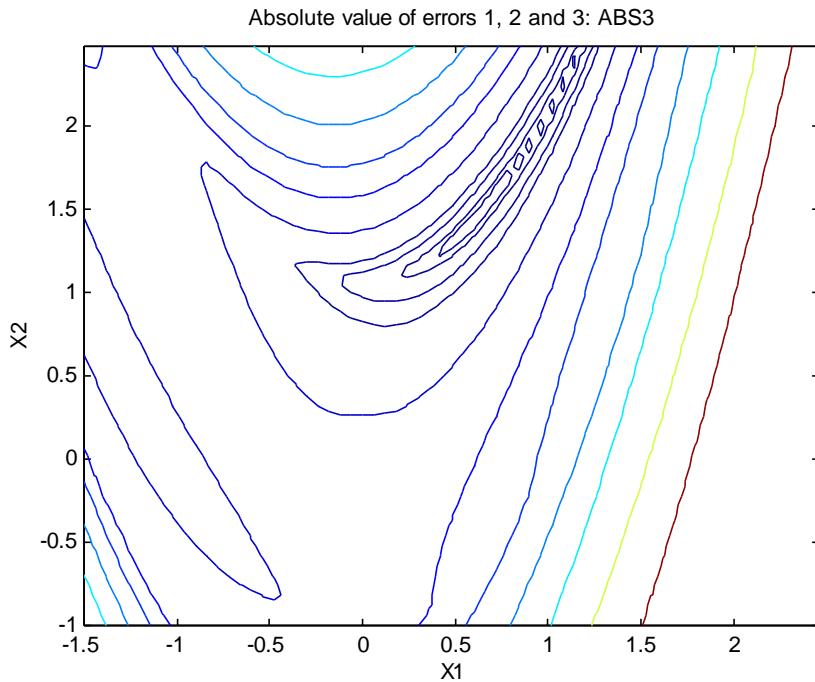
$$\mathbf{u} = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} = \begin{bmatrix} 1.1 & -0.2 \\ 0.2 & 0.9 \end{bmatrix} \mathbf{x} + \begin{bmatrix} -0.3 \\ 0.3 \end{bmatrix}$$



## First $l_1$ Parameter Extraction



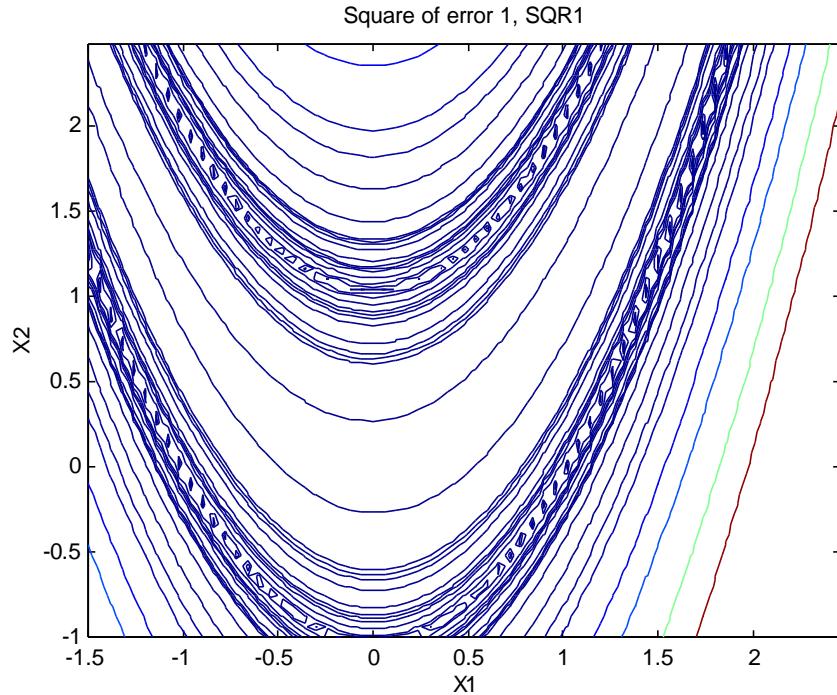
(a) single point parameter extraction



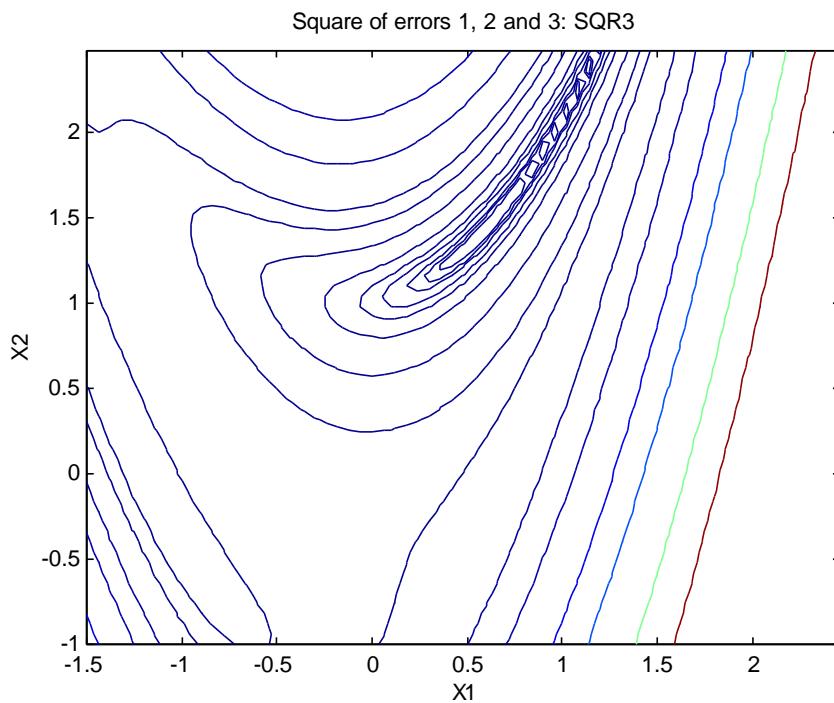
$$\mathbf{x}_c^{(1)} = \begin{bmatrix} 0.6 \\ 1.4 \end{bmatrix}$$

(b) multiple point parameter extraction (2 additional points)

## First $l_2$ Parameter Extraction



(b) single point parameter extraction



$$\mathbf{x}_c^{(1)} = \begin{bmatrix} 0.6 \\ 1.4 \end{bmatrix}$$

(b) multiple point parameter extraction (with 2 additional points)

## Space Mapped Solution

$$Step \ 0. \quad \mathbf{x}_f^{(1)} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \ \mathbf{B}^{(1)} = \mathbf{I}, \ j=1$$

$$Step \ 1. \quad R_f(\mathbf{x}_f^{(1)}) = 108.32$$

$$Step \ 2. \quad \text{When } \mathbf{x}_c^{(1)} = \begin{bmatrix} 0.6 \\ 1.4 \end{bmatrix}, \ R_c(\mathbf{x}_c^{(1)}) = R_f(\mathbf{x}_f^{(1)})$$

$$Step \ 3. \quad \mathbf{f}^{(1)} = \begin{bmatrix} 0.6 \\ 1.4 \end{bmatrix} - \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} -0.4 \\ 0.4 \end{bmatrix}$$

$$Step \ 4. \quad \text{Since } \mathbf{B}^{(1)} = \mathbf{I}, \ \mathbf{h}^{(1)} = \begin{bmatrix} 0.4 \\ -0.4 \end{bmatrix}$$

$$Step \ 5. \quad \text{Set } \mathbf{x}_f^{(2)} = \begin{bmatrix} 1 \\ 1 \end{bmatrix} + \begin{bmatrix} 0.4 \\ -0.4 \end{bmatrix} = \begin{bmatrix} 1.4 \\ 0.6 \end{bmatrix}$$

$$Step \ 6. \quad R_f(\mathbf{x}_f^{(2)}) = 1.8207$$

$$Step \ 7. \quad \text{When } \mathbf{x}_c^{(2)} = \begin{bmatrix} 1.12 \\ 1.12 \end{bmatrix}, \ R_c(\mathbf{x}_c^{(2)}) = R_f(\mathbf{x}_f^{(2)})$$

$$Step \ 8. \quad \mathbf{f}^{(2)} = \begin{bmatrix} 1.12 \\ 1.12 \end{bmatrix} - \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 0.12 \\ 0.12 \end{bmatrix}$$



Step 9.  $\mathbf{B}^{(2)} = \mathbf{B}^{(1)} + \frac{\mathbf{f}^{(2)} \mathbf{h}^{(1)T}}{\mathbf{h}^{(1)T} \mathbf{h}^{(1)}} = \begin{bmatrix} 1.15 & -0.15 \\ 0.15 & 0.85 \end{bmatrix}$

Step 4b.  $\mathbf{h}^{(2)} = -\mathbf{B}^{(2)-1} \mathbf{f}^{(2)} = \begin{bmatrix} -0.12 \\ -0.12 \end{bmatrix}$

Step 5b. Set  $\mathbf{x}_f^{(3)} = \begin{bmatrix} 1.4 \\ 0.6 \end{bmatrix} + \begin{bmatrix} -0.12 \\ -0.12 \end{bmatrix} = \begin{bmatrix} 1.28 \\ 0.48 \end{bmatrix}$

Step 6b.  $R_f(\mathbf{x}_f^{(3)}) = 0.1308$

Step 7b. When  $\mathbf{x}_c^{(3)} = \begin{bmatrix} 1.012 \\ 0.988 \end{bmatrix}$ ,  $R_c(\mathbf{x}_c^{(3)}) = R_f(\mathbf{x}_f^{(3)})$

Step 8b.  $\mathbf{f}^{(3)} = \begin{bmatrix} 1.012 \\ 0.988 \end{bmatrix} - \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 0.012 \\ -0.012 \end{bmatrix}$

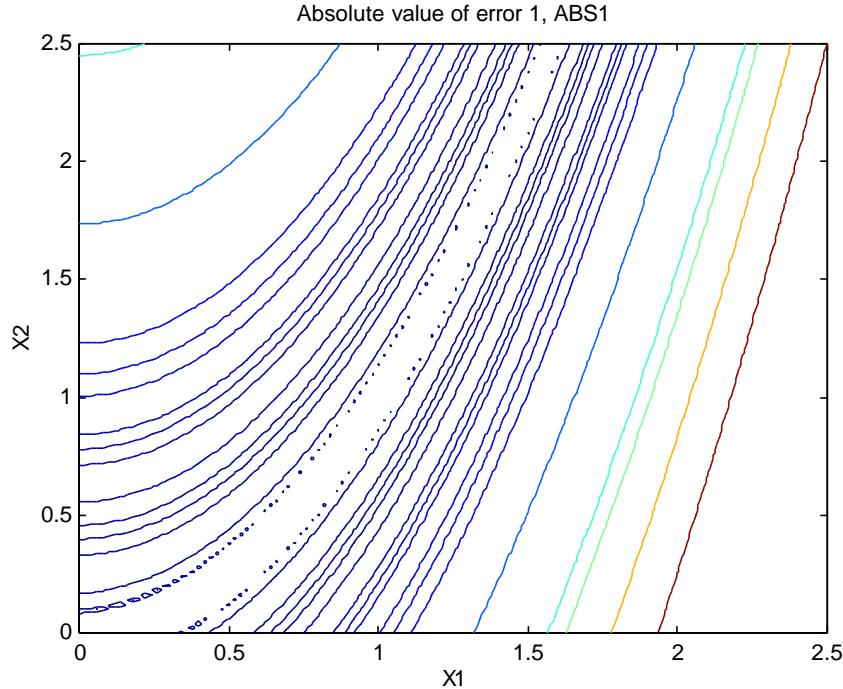
Step 9b.  $\mathbf{B}^{(3)} = \mathbf{B}^{(2)} + \frac{\mathbf{f}^{(3)} \mathbf{h}^{(2)T}}{\mathbf{h}^{(2)T} \mathbf{h}^{(2)}} = \begin{bmatrix} 1.1 & -0.2 \\ 0.2 & 0.9 \end{bmatrix}$

Step 4c.  $\mathbf{h}^{(3)} = -\mathbf{B}^{(3)-1} \mathbf{f}^{(3)} = \begin{bmatrix} -0.0082 \\ 0.0151 \end{bmatrix}$

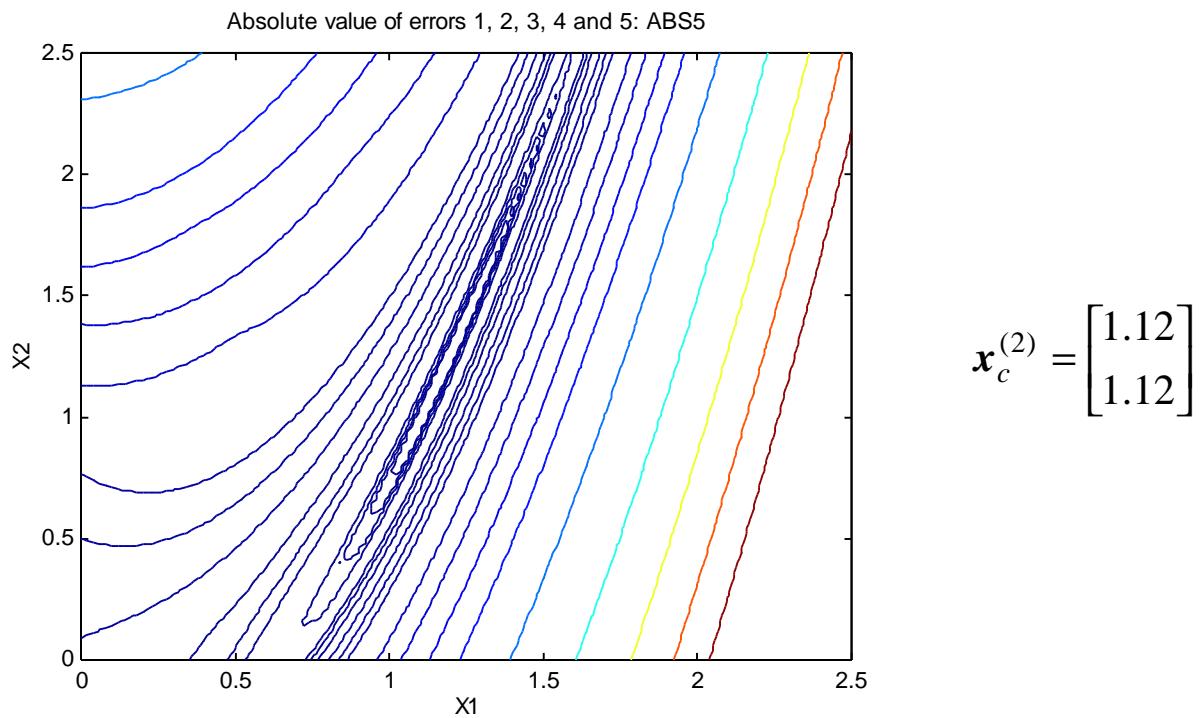
Step 5c. Set  $\mathbf{x}_f^{(4)} = \begin{bmatrix} 1.28 \\ 0.48 \end{bmatrix} + \begin{bmatrix} -0.0082 \\ 0.0151 \end{bmatrix} = \begin{bmatrix} 1.2718 \\ 0.4951 \end{bmatrix}$

Step 6c.  $R_f(\mathbf{x}_f^{(4)}) = 0$ , then  $\bar{\mathbf{x}}_f = \mathbf{x}_f^{(4)}$  and the algorithm ends

## Second $l_1$ Parameter Extraction

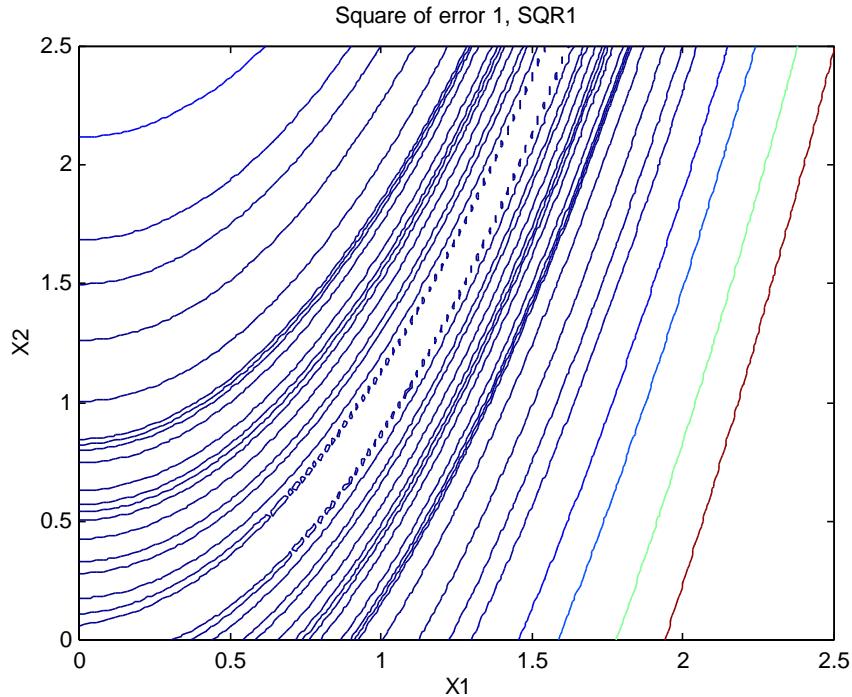


(a) single point parameter extraction

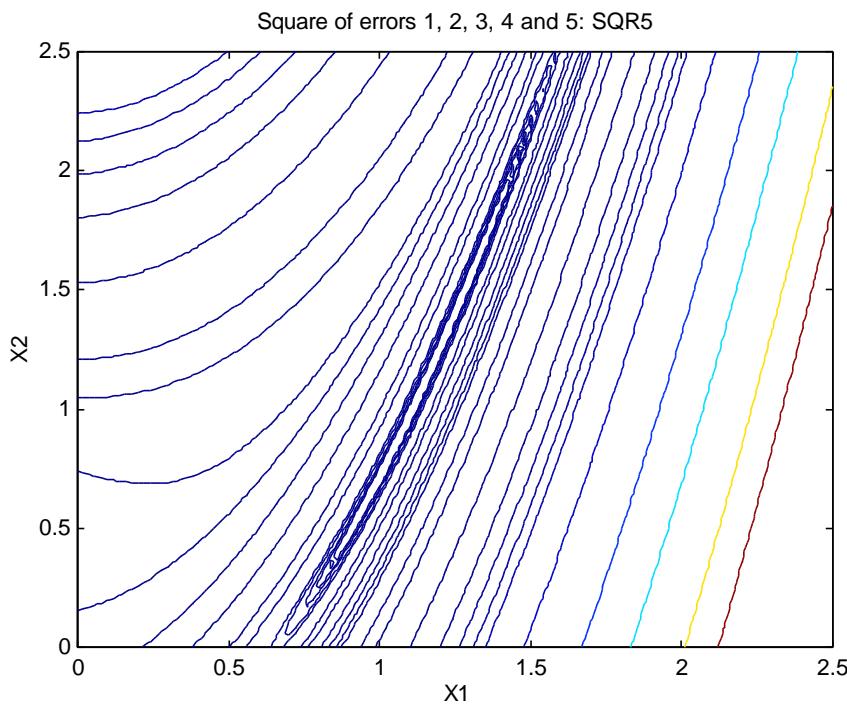


(b) multiple point parameter extraction (4 additional points)

## Second $l_2$ Parameter Extraction



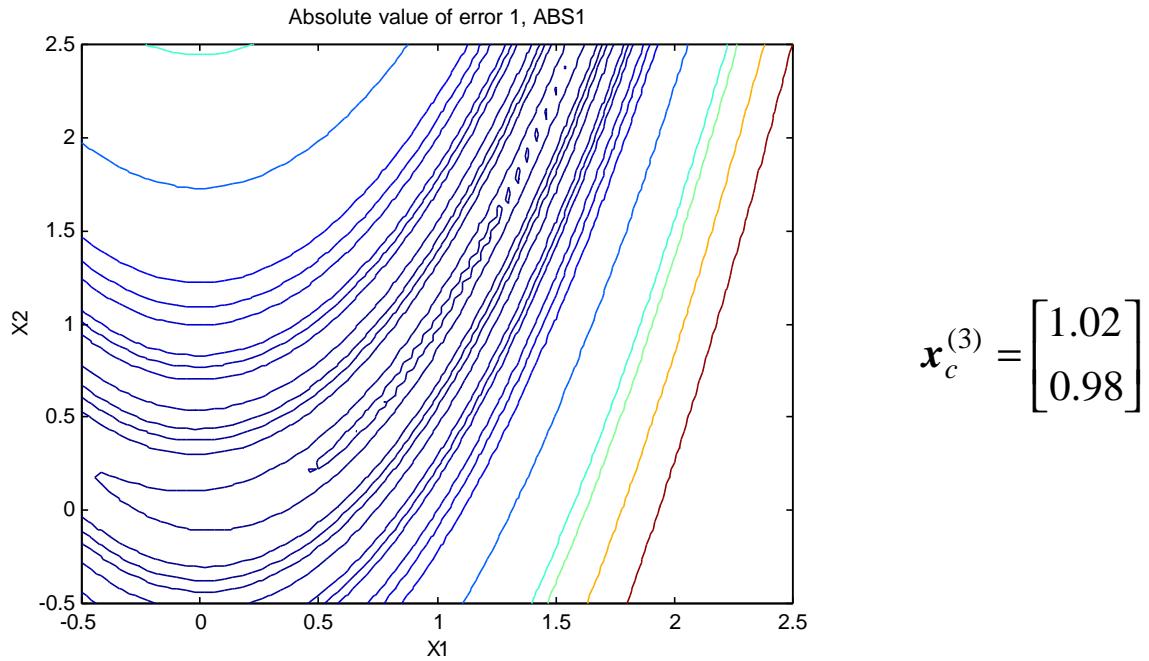
(b) single point parameter extraction



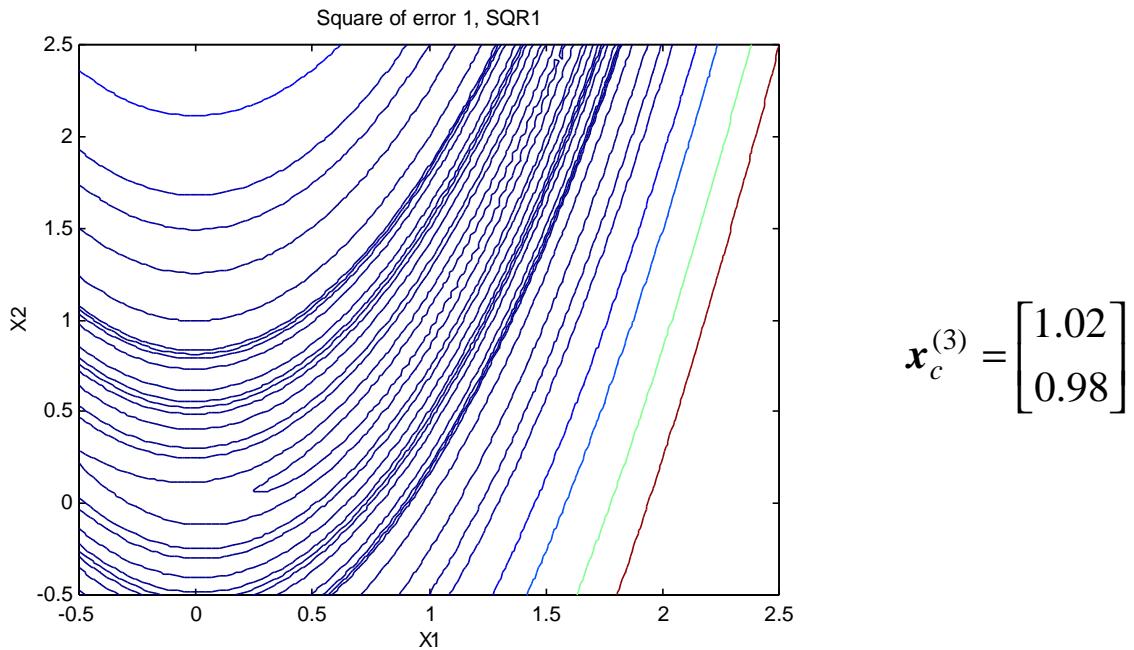
$$x_c^{(2)} = \begin{bmatrix} 1.12 \\ 1.12 \end{bmatrix}$$

(b) multiple point parameter extraction (with 4 additional points)

## Third Parameter Extraction



(a) single point  $l_1$  parameter extraction



(b) single point  $l_2$  parameter extraction



## Conclusions

the Aggressive Space Mapping (ASM) algorithm with multiple point parameter extraction was illustrated making use of two analytical Rosenbrock functions

the improvement in the uniqueness of the parameter extraction due to multiple point matching was graphically illustrated

the sizes and directions of the  $\Delta\mathbf{x}_i$  used for multiple point parameter extraction affects the degree of improvement in the uniqueness of the parameter extraction solution

the ASM algorithm was executed in a step by step fashion, and the corresponding space mapped solution was accomplished after only one SM iteration for the case of shifting in the input parameters, and after three SM iterations for the case of shifting, scaling and rotation of the input parameters

the mapping calculated by the ASM algorithm is equal to the original linear mapping between both parameter spaces