



Optimizing the WTLS cost function

- In the previous lesson, found WTLS cost function to optimize
- To find \hat{Q} to minimize this cost function, set $\partial \chi_{\text{WTLS}}^2 / \partial \hat{Q} = 0$

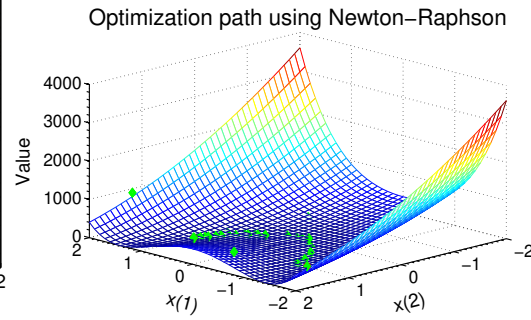
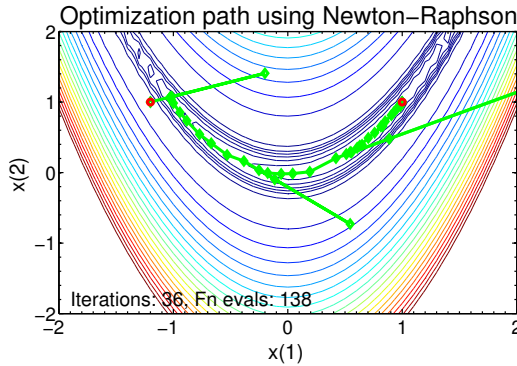
$$\frac{\partial \chi_{\text{WTLS}}^2}{\partial \hat{Q}} = \sum_{i=1}^N \frac{2(\hat{Q}x_i - y_i)(\hat{Q}y_i\sigma_{x_i}^2 + x_i\sigma_{y_i}^2)}{(\hat{Q}^2\sigma_{x_i}^2 + \sigma_{y_i}^2)^2} = 0 \quad (\text{via Mathematica})$$

- Unfortunately, this solution has none of the nice properties of the WLS solution:
 1. There is no closed-form solution in the general case
 2. There is no recursive update in the general case
 3. There is no fading memory recursive update



1. No closed-form solution

- A numerical method must be used to find \hat{Q}



- One possibility is to perform a Newton–Raphson search for \hat{Q}



Newton–Raphson search

- Every time new (x_i, y_i) available, perform several iterations of

$$\hat{Q}_k = \hat{Q}_{k-1} - \left(\partial \chi_{\text{WTLS}}^2 / \partial \hat{Q} \right) / \left(\partial^2 \chi_{\text{WTLS}}^2 / \partial \hat{Q}^2 \right)$$

- Numerator is “Jacobian” of original cost function, given by earlier equation
- Denominator is “Hessian” of original cost function, which can be shown to be

$$\frac{\partial^2 \chi_{\text{WTLS}}^2}{\partial \hat{Q}^2} = 2 \sum_{i=1}^N \frac{\sigma_{y_i}^4 x_i^2 + \sigma_{x_i}^4 (3\hat{Q}^2 y_i^2 - 2\hat{Q}^3 x_i y_i) - \sigma_{x_i}^2 \sigma_{y_i}^2 (3\hat{Q}^2 x_i^2 - 6\hat{Q} x_i y_i + y_i^2)}{(\hat{Q}^2 \sigma_{x_i}^2 + \sigma_{y_i}^2)^3}$$

- Search initialized with prior WLS estimate of \hat{Q} , and is guaranteed to converge to global solution since cost function χ_{WTLS}^2 is convex
- Number of significant figures in the solution doubles with each iteration
 - Around four iterations produce double-precision results



2. No recursive update

- There is no recursive update in the general case: this has storage implications and computational implications
 - To use WTLS, the entire vector x and y must be stored, which implies increasing storage as the number of measurements N increases
 - Furthermore, the number of computations grows as N grows
- Not well suited for an embedded-system application that must run in real time with limited storage capabilities



3. No fading-memory recursive update

- No fading memory recursive update (no recursive update)
- *Non-recursive* fading memory cost function may be defined

$$\chi_{\text{FMWTLS}}^2 = \sum_{i=1}^N \gamma^{N-i} \frac{(y_i - \hat{Q} x_i)^2}{\hat{Q}^2 \sigma_{x_i}^2 + \sigma_{y_i}^2}$$

- The Jacobian of this cost function can be found to be

$$\frac{\partial \chi_{\text{FMWTLS}}^2}{\partial \hat{Q}} = 2 \sum_{i=1}^N \gamma^{N-i} \frac{(\hat{Q} x_i - y_i)(\hat{Q} y_i \sigma_{x_i}^2 + x_i \sigma_{y_i}^2)}{(\hat{Q}^2 \sigma_{x_i}^2 + \sigma_{y_i}^2)^2}$$



3. No fading-memory recursive update

- The Hessian of the cost function can be found to be

$$\frac{\partial^2 \chi_{\text{FMWTLS}}^2}{\partial \hat{Q}^2} = 2 \sum_{i=1}^N \gamma^{N-i} \left(\frac{\sigma_{y_i}^4 x_i^2 + \sigma_{x_i}^4 (3\hat{Q}^2 y_i^2 - 2\hat{Q}^3 x_i y_i)}{(\hat{Q}^2 \sigma_{x_i}^2 + \sigma_{y_i}^2)^3} - \frac{\sigma_{x_i}^2 \sigma_{y_i}^2 (3\hat{Q}^2 x_i^2 - 6\hat{Q} x_i y_i + y_i^2)}{(\hat{Q}^2 \sigma_{x_i}^2 + \sigma_{y_i}^2)^3} \right)$$

- Can use Newton–Raphson search to minimize cost function to find \hat{Q}



Summary

- WTLS has none of the nice properties of the WLS solution:
 1. There is no closed-form solution in the general case
 2. There is no recursive update in the general case
 3. There is no fading memory recursive update
- Can use Newton–Raphson search, but requires growing memory and computation
- Next week, you will learn special case of WTLS that gives a closed-form solution, with recursive update, and fading memory
- Leads to approximate solution to general WTLS that also has these nice properties
- But first, we consider an important property of both the WLS and WTLS solutions